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DIE DYNAMIK DER RENTABILITÄT ALS STOCHASTISCHER PROZESS-EINE EMPIRISCHE ZEITREIHENANALYSE VON AUSGEWÄHLTEN DEUTSCHEN UND AMERIKANISCHEN UNTERNEHMEN

Vom Fachbereich 20 Informatik

der Technischen Universität Berlin

zur Erlangung des akademischen Grades eines

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genehmigte Dissertation

Vorgelegt von Diplom-Informatiker Talat Mahmood aus Lahore, Pakistan Berlin 1990 D83

Promotionsausschuß:

Vorsitzender: Prof. Dr. G. Hommel, FB 20

Berichter: Prof. Dipl. Math. R.K. Bauer, FB 20

Prof. Dr. J. Schwalbach, FU Berlin

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ABSTRACT

Title : " The Dynamics of Profitability as a Stochastic Process- An Empirical Time Series Analysis of Selected German and US Firms."

The objective of this thesis is to study time series of company profit rates as a stochastic process. The study departs from previous studies which have predominantly used the polynomial convergence and partial adjustment models. It examines whether the adjustment process, as it is specified in the partial adjustment model to describe the long run convergence of firms profit rates, is really of the first order. In this context the theory of time series analysis is then illustrated in order to test whether current profits depend on profits in more than one period, and whether the profit convergence process can be of a different form, for example, moving average, autoregressive, or the mixed autoregressive—moving average form. The univariate stationary time series models are used to evaluate two samples of 299 firms for the FRG and 500 U.S. firms. Further, the determination of the order of mixed form is a difficult part of the time series analysis. Several methods for determining the order for mixed processes have been proposed in the literature. The method of Extended Sample Autocorrelation Function (ESACF) is evaluated and applied. The major advantage of this approach is that it eliminates the need to determine the order of differencing in order to produce stationarity in modeling time series.

Comparing the results of different stochastic models and of the PA model, it is found that:

a) The numerical accuracy of the estimation method of stochastic models raises the estimates of the persistence of long run profits particularly for the most profitable and less profitable subgroups across all stochastic models for both countries. This implies that profitability differences exist at least for the lowest and highest subgroups, but they are higher in the US then the FRG.; b) The model selection test revealed that the most significant results were for the first order autoregressive- moving average model for the FRG and, in addition to the ARMA for the third order autoregressive model for the US.;

c) The speed of adjustment is higher across all stochastic models in the FRG than in the US, i.e., a high (low) speed of adjustment tends to lower (high) the persistence of profits, which implies that the persistence is more strongly evident for US than the FRG.;

d) If only statistically significant equations are considered in the analysis, the persistence of profits increases substantially for both countries.;

e) Stronger evidence is found for the significance of a first order lag for both countries, but in addition to the first order lag for a number of firms a higher order lag is also statistically significant from zero for the US.; and

f) The results of the identification technique (ESACF) show that this procedure is not fully operational for a small sample but identifies a moving average of first order for a relatively large number of firms for both countries.;

INTRODUCTION

Several empirical studies based on cross-sections have examined the relationship between market structure and performance. These studies do not reveal whether the observed relationship captures the market dynamics. Indeed, the lack of attention paid to long run consideration might give rise to incorrect structure-performance results. A very few economists have considered the *dynamics* of the relationship between market structure and performance in their empirical studies. Stigler's (1963) work was among the first. Later, Qualls (1974) and more recently Mueller(1986) tested the *hypothesis* that " If the company's profit rates converges to a normal or competitive level, "excess" profits disappear in the long run, then it is to see, whether these "excess" profits differ across companies", i.e., a company with a high (low) initial profit rate tends to earn a high (low) profit rate, implying a persistence of intercompany profit- rate differences (For the discussion about process of competition and persistence, see Mueller(1990), and Geroski and Mueller (1990)).

Qualls's study is based on two U.S. data samples, one with 30 industries over sixteen years and another with 220 firms over eighteen years. He observed a convergence in profits within a barrier- to- entry group but not across groups. Mueller's results for the U.S confirm Quall's findings. He applied a different test methodology and used the Federal Trade Commission (FTC) company survey data sample with 600 firms over 23 years, 1950 – 1972. Mueller found a convergence process " ... to lower (higher) profit levels for the companies with highest (lowest) initial profit ranks...but ... the convergence is incomplete." (Mueller (1986), p.23). The most recent results were achieved by the persistence of profit (POP) international team, in which comparisons across countries are made. (see Mueller ed. (1990)). All these studies applied the partial adjustment model(PA-model see section 1.2) to describe the long run convergence process of individual firms profit rates. This PA-model was first purposed by Odagiri and Yamawaki(1986), who also used polynomial models (see also Mueller (1977)) to explain this hypothesis, but they found various disadvantages of the polynomial models

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(i.e., the profit rate is regressed on the inverse of time, also on its quadratic and cubic form) in the sense that the estimates are not free from the choice of unit to measure time.

The period—to—period change in 1/t (i.e., 1/t = 1, 0.5, 0.25, 0.17,.....,0.063, 0.059) is relatively large during the first two to three periods but afterwards is small. This suggests that, on the one hand, the estimates of the slope coefficient will be more strongly influenced by the profit rates during the first several years while, on the other hand, the estimates of the intercept will be more strongly influenced by the profit rate in later years. In this sense a fairly rapid convergence, if any, of the profit rate is presupposed in the model. This disadvantage can be resolved if the partial adjustment model having the desired convergence properties is used.

However, the partial adjustment model, which assumes an adjustment lag of only one period, is not without any problems. If the lagged values of the dependent variable in the PA—model appear as regressors, ordinary least square estimation produces biased and generally inconsistent results, when the error term follow a first or higher order autoregressive process (see Zellner, et.el.(1965), Maddala and Vogel(1967), Zellner and Geisel(1970), Koutsoyiannis (1977), p.304–309, Breusch(1978), Kiviet (1986)). Dielman, et.el. (1989) recently show that the efficiency advantage of using Prais—Winston (PW)— estimator, which corrects for the autocorrelations, rather than OLS when disturbances are highly autocorrelated. The POP—studies do not make any explicit assumptions about the error term and also consider statistically insignificant equations in their analysis. In this context various tests of model specification are proposed in the literature (see Durbin(1970)). For this study the Lagrange—multiplier—test(LM) for first and higher order autocorrelation (Breusch and Godfrey(1981)) is applied to both the US and FRG samples.

Based on our qualifications with respect to the polynomial and PA-models we propose some alternative models, which consider a higher order adjustment and use more information from their parameters.

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We believe that these models are better suited for analyzing the dynamics of corporate profits over long time periods and capture better the unexplained variance of the error term as well the incomplete structural misspecification. We consider profit rate time series as a stochastic process which is characterized by stationary properties.

In this context we extend our analysis to the univariate Box—Jenkins time series analysis, which considers only the past history of the variable itself in explaining the relationship. First, we will only model the profit rate as autoregressive of first, second and third order and then as a mixed form autoregressive—moving average of first order. The parameters of these models will be transformed so that the speed of adjustment can be approximated and the long run profit level can be estimated.

Univariate model- building has been explicitly used for the purpose of short term economic forecasting (for the purpose of prediction see Leiner (1985)). In several studies a comparison (see Prothero and Wallis (1976), Jenkins (1979), Part.4 and Tu (1981)) is made between univariate time series forecasting and forecasting accuracy based on econometric modeling. Some studies show that the univariate time series modeling technique achieves more accurate results than econometric modeling. Nelson (1973) showed that the forecast accuracy of univariate models is often higher than more complex macro-economic econometric modeling. Makidakis and Hiblon (1979) also examined 111 time series and out of eight different univariate modeling techniques employed, the Box- Jenkins approach had the highest accuracy. Similar conclusions were also found in other studies (see Naylor et.el.(1972), Newbold and Granger (1974), Guerts and Ibrahim (1975), Kyle (1978), Friedrich and Termin (1983), and Pfister(1984). In contrast, other studies (for example, Eckstein 1983) showed that the time series procedure is not better than the econometric model. Heilman and Neuhaus (1987) compared the short-term forecasting accuracy of a multi- equation ARIMA model and of a medium sized econometric model. They found that the econometric model is superior to the time series models in most variables.

In a survey article, Wolters (1987) argues that strong dependencies exist between both methods contrary to the widely held view that these approaches have little in common.

Secondly, in determining the real order and nature of the underlying process of the time series, we will not apply the usual identification technique based on the autocorrelations and partial autocorrelation described in Box-Jenkins(1976). An alternative method of extended sample autocorrelation function ((ESACF), see Tsay and Tiao (1984)) is developed and applied to both samples. Various methods for identifying the orders of the models are proposed in the literature (see section 4.). Finally, the results of all stochastic models will be compared also with PA-model in order to see whether they differ across models and whether the accuracy of results is improved.

The *purpose* of this study is not to question the POP- studies, but to extend the analysis using a different time series methodology in order to see whether the quality of results is thereby improved.

The thesis is organized in two parts : 1) Theoretical and 2) Empirical.

The *theoretical* part has three sections: Section one describes the deterministic models and presents the appropriate tests procedures. In section two the theory of univariate time series models is discussed and a test of lag structure is constructed. In section three the identification method and extended sample autocorrelation function (ESACF), is derived and the diagnostic check procedures are explained.

The *empirical* part has four sections: Section one describes the data, variables and the definitions of profit rates and then reports the empirical results obtained from estimating deterministic models and specification tests applied to them. Further, in section two we report the results of stochastic models and the results of different tests applied to them for both the FRG and the US samples. In the next section the results of using the identification technique and the estimation results from the identified models are reported. Finally, a comparison is made between the PA- model and stochastic models and the results by industry for the two countries are discussed.

THEORETICAL PART :

1 Deterministic Models :

1.1 Polynomial Models

The following polynomial model has the convergence property that the limit of Π_{it} is finite as t goes to infinity (will be called in our analysis the " *standard model (ST)*)". This model has already been used by Mueller (1986), and by Odagiri and Yamawaki (1986) and is as follows: (see Figure 1.1).

(1)
$$\Pi_{it} = \alpha_i + \beta_i/t + \epsilon_t$$

where Π_{it} is the normalized profit rate. This is calculated as : $\Pi_{it} = (P_{it} - \bar{P}_t) / \bar{P}_t$, where P_{it} is the observed profit rate and $\bar{P}_t = \sum_{i=1}^{n} P_{it} / n$, the average profit rate. Further, α_i is a proxy for the permanent advantage of firm i, and β_i the speed of adjustment of firm i. The inverse of time is used, because the coefficient β_i will diminish as t goes to infinity. Odagiri and Yamawaki (1986) argued that model (1) assumes a monotonic convergence of Π_{it} to α_i , but in some cases the convergence is not monotonic which is why they also used two alternative models with higher- order coefficients γ_i and δ_i . The models are as follows: (see Figure 1.1)

(2)
$$\Pi_{it} = \alpha_i + \beta_i / t + \gamma_i / t^2 + \varepsilon_i$$

(3)
$$\Pi_{it} = \alpha_i + \beta_i / t^2 + \delta_i / t^3 + \varepsilon_t$$

According to Mueller the "best fit model (BF) " among these three models (1), (2) and (3), is defined for each company as the one which yields the highest R^2 , so the best fit model may also vary across companies.



The curves correspond to the following equational forms:

(1)
$$\pi_{it} = \alpha_i + \beta_i/t, \beta_i > 0$$

(2)
$$\pi_{it} = \alpha_i + \beta_i/t + \gamma_i/t^2$$
, $\beta_i < 0$, $\gamma_i > 0$

(3)
$$\pi_{it} = \alpha_i + \beta_i/t + \gamma_i/t^2 + \delta_i/t^3$$
,
 $\beta_i > 0, \gamma_i < 0, \delta_i > 0$

Figure 1.1

1.2 Partial adjustment model

According to Odagiri and Yamawaki (1986) the disadvantages of polynomial models (see also introduction p.3) can be resolved if we use a partial adjustment model, which has been extensively used in studies of investment behavior and money demand and several persistence of profits studies (see Mueller ed. (1990)). With this model the dynamic adjustment process can be well explained. Howrey and Quandt (1967) have examined the theoretical properties of this type of adjustment process and shown them to be stable.

Now in order to derive the model for estimation, let the adjustment equation be as follows:

(4)
$$\Pi_{it} - \Pi_{it-1} = \lambda (\Pi_{it} - \Pi_{it-1})^{*},$$

where Π_{it} is the observed profit rate and Π_{it}^{*} is expected profit rate, which has to be approximated, since we know that the expectations are not observable and λ is the adjustment parameter.(For practical difficulties of distinguishing between different lag scheme and lag models, See Griliches(1967), Kennan(1979)).

¹ $\Pi_t - \Pi_{t-1} = \lambda (\Pi_t^* - \Pi_{t-1})$ now from the above equation we have $\Pi_t = \lambda \Pi_t^* + (1 - \lambda) \Pi_{t-1}$ now let $\lambda \Pi_t^* = \alpha$ and $\beta = 1 - \lambda$ then $\Pi_t^* = \alpha / \lambda$ and $\lambda = 1 - \beta$, it follows that $\Pi_t^* = \alpha / 1 - \beta$ and $\lambda = 1 - \beta$,

we can now insert these values in eq.(4) and get $\hat{\alpha}$ and $\hat{\beta}$ the OLS estimates.

We can now derive the testable model from the above equation (4) as:

(5)
$$\Pi_{it} = \frac{\alpha}{1-\beta} + (1-\beta) \Pi_{it-1} + \varepsilon_t$$

where $\alpha / 1 - \beta$ represent the long run estimated profit rate and $(1 - \beta)$ denotes the convergence or speed of adjustment (For an alternative dynamic model, see Schwalbach, et.el. (1987)).

The model which we actually estimate is as follows:

(6)
$$\Pi_{it} = \alpha + \beta \Pi_{it-1} + \varepsilon_t$$

We estimate the parameters α and β from eq.(6) and insert these values in eq.(5) to get the actual estimates. In the context of the partial adjustment model the speed of adjustment parameter $\lambda = (1 - \beta)$ should fulfill the following condition $0 < \lambda < 1$: close to zero means that the adjustment is supposed to be slow and λ close to one that there is faster or complete adjustment(see also Schwalbach (1982)).

The four possible adjustment time paths see Schohl (1989) are shown in the figure 1.2:



Profitability Time Paths of the Partial Adjustment Model

•

1.3 Nonlinear restrictions

The partial adjustment model we want to estimate contains nonlinear restrictions¹ and is described again as

(7)
$$\Pi_{it} = \frac{\alpha}{1-\beta} + (1-\beta) \Pi_{it-1} + \varepsilon_t$$

It should explain the adjustment process of profitability movements. In the model mentioned above there are two **restricted** parameters α and β . The actual model with **unrestricted** parameters and which we actually estimate is

(8)
$$\Pi_{it} = \alpha + \beta \Pi_{it-1} + \varepsilon_t$$

In the following we now relate the parameters of the model (8) with (7) such as

(9)
$$\hat{\alpha} = \frac{\alpha}{1-\beta}$$
 and $\hat{\beta} = 1-\beta$

We see that $\hat{\alpha}$ and $\hat{\beta}$ are **nonlinear** functions of the unrestricted parameters. In model (8) we have Π_{it-1} on the right hand side, so that the unconstrained estimators are not unbiased, this implies that none of the constrained estimators can be claimed as unbiased. So, we have to approximate the large sample variance of $\hat{\alpha}$ with the following formula:

(10)
$$\operatorname{Var}\left(\hat{\alpha}\right) \approx \left[\frac{1}{1-\hat{\beta}}\right]^{2} \operatorname{Var}\left(\hat{\alpha}\right) + \left[\frac{\hat{\alpha}}{1-\hat{\beta}}\right]^{2} \operatorname{Var}\left(\hat{\beta}\right)^{2} + 2\left[\frac{1}{1-\hat{\beta}}\right] \left[\frac{\hat{\alpha}}{(1-\hat{\beta})}2\right] \operatorname{Cov}\left(\hat{\alpha},\hat{\beta}\right)$$

We then calculate the standard error of the formula mentioned above and apply the usual significance test in order to confirm the significance of the estimated parameters of the equation (7).

¹ see Kmenta (1971), p. 442 – 445, see also Mueller(1990).

2. Model specification

Of the various kinds of misspecification encountered in econometric modeling, the *autocorrelation* has received particular attention. Breusch (1978) describes, that if the disturbances of a linear model are autocorrelated, the application of ordinary least square (OLS) produces unbiased but inefficient estimates. However, if the relationship is of a dynamic nature, where the lagged values of the dependent variable appear as regressors, OLS gives generally inconsistent and biased estimates. The standard tests based on residuals, of Durbin and Watson (1950,51), Schmidt (1972) and Wallis (1972) are then invalid. Granger and Newbold (1974), Hendry (1975) describe the major consequences of autocorrelated errors and dynamic misspecifications. Several studies have proposed specification tests of dynamic relationships (see Durbin 1970, Godfrey 1978 and Breusch and Pagan 1980) and other developments are summarized in Harvey (1981). Kiviet (1986), in his simulation study of various tests for serial correlation and predictive failure in models with lagged dependent variables, finds many tests defective in small samples (see also Thursby(1981). In the following we describe Lagrange Multiplier (LM) test shortly (For a brief discussion how the test is derived see Breusch and Godfrey(1981)).

2.1 Lagrange multiplier

For the lagrange multiplier(LM) approach to testing for autocorrelation, a simple regression model with first order *autocorrelated* errors is considered as follows:.

(11)
$$Y_t = \beta X_t + \mu_t$$
, where $t = 1, 2, ..., n$ and

(12)
$$\mu_t = \rho \,\mu_{t-1} + \varepsilon_t$$

where ε_t , NID $(0, \sigma_{\varepsilon}^2)$ with $|\rho| < 1$. This means that if $\rho = 0$ then μ_t are independent, otherwise they are autocorrelated.

Breusch and Godfrey (1981) show that LM tests for autocorrelation can be viewed as least square tests of the joint significance of the estimated regression coefficients, requiring only the estimation of an additional regression equation by OLS. Suppose the model is as follows :

(13)
$$Y_{t} = \sum_{i=1}^{k} \beta_{i} Y_{t-i} + \mu_{t}$$

where $t = 1, 2, \dots, n$ and Y_{t-i} are the lagged values of Y_t , and we wish to test the assumption that the μ_t are independent against a pth order autocorrelation alternative. Breusch (1978a) and Godfrey (1978c) show that the LM-statistics can also be calculated as the product of the sample size, n, and the R² statistics from the regression of the OLS residuals $\hat{\mu}$ on its first p lagged values $\hat{\mu}_{t-1}, \dots, \hat{\mu}_{t-p}$ and the original regressor Y_{t-i} . The null hypothesis of independent errors can be tested against pth order AR or MA models by adding the first p lagged values of $\hat{\mu}_t$ to the regressors of the economic model, which looks like

(14)
$$Y_{t} = \sum_{i=1}^{k} \delta_{i} Y_{t-i} + \sum_{i=1}^{p} \rho_{i} \hat{\mu}_{t-i} + \eta_{t} \text{ where } t = 1, 2,, n$$

and then applying any asymptotically valid form of the usual test of the joint significance of the estimated ρ_i - coefficients.

2.2 The Test

The null hypothesis of serial independence of the regression errors will be tested against pth-order autoregressive or moving average models by adding the first p lagged values of $\stackrel{\wedge}{\mu}$ to the regression models as follows:

(15)
$$Y_t = \alpha + \beta Y_{t-1} + \sum_{j=1}^p \rho_j \hat{\mu}_{1t-j} + \eta_t,$$

where $|\hat{\rho}_j| < 1$, and if $\hat{\rho}_j = 0$, then the error term is serially independent.

null hypothesis :

$$\begin{aligned} H_0 &: \rho_1 = 0 \\ H_0 &: \rho_1 = \rho_2 = 0 \\ H_0 &: \rho_1 = \rho_2 = \rho_3 = 0 \end{aligned}$$

against H_a and a conventional F-- test can be applied.

3. Stochastic models

In the previous chapter we presented the polynomial and partial adjustment models, in which the PA – model assumed the adjustment lag of only one period. In this section we extend our analysis to more elaborate models from the class of univariate time series analysis¹. With such models we want to test whether an adjustment lag can be longer than one period and whether a process which a time series generates can be of a different form, like autoregressive, moving average or of mixed form such as autoregressive – moving – average.

These sorts of modeling are conducted by the theory of stochastic process, which assumes that the observed time series $Z_1,...,Z_t$ is drawn from a set of jointly distributed random variables: i.e., there exists some probability distribution function $F(Z_1,...,Z_t)$ that assigns probabilities to all possible combinations of $Z_1,...,Z_t$ (see Pindyck and Rubinfeld (1981), p.494). Furthermore, if the underlying process can be assumed to be invariant with respect to time, than it is said to be stationary, i.e., the probability distribution $F(Z_t)$ is the same for all time t. Then the mean, variance and covariance are invariant with displacement in time otherwise non-stationary. In the literature very common processes, which can be described as non-stationary models, are Interest Rate, GNP, Inventory, etc.. These models can be transformed into stationary models with the help of widely used method of differencing and their order is identified with the help of autocorrelation and partial autocorrelation functions, we will discuss the identification methods in section 4.

3.1 The discrete stochastic process

A discrete stochastic process can be defined as a random vector $Z_1, Z_2,...,Z_t$ with the joint distribution function $F(Z_1, Z_2,...,Z_t)$ and density $p(z_1,...,z_t)$.

¹For a short review see Pfister(1984), Nienstedt(1984), and studies such as Box and Jenkins (1976), Vandaele(1983), Schlittgen and Streitberg(1984), Brockwell and Davis(1987), see also for overview Heiler (1981), Newbold (1981).

In practice it is unknown to derive such distribution function, i.e., where the process is described by its two moment functions the *mean* and the *autocovariance* functions.

The mean is given as follows:

$$\mu = E [Z_{\downarrow}]$$

and the *autocovariance* as:

$$\gamma_{t,s} = Cov(Z_t, Z_s) = E[(Z_t - \mu_t) (Z_s - \mu_s)]$$

so that the $\gamma_{t,t}$ describes the variance function.

As we know that in reality it is not possible to achieve for each time period t the mean and the variance. That's why the hypothesis are formulated with respect to displacement in time for mean and the covariance. The most common assumption is the *stationarity* of the process.

3.2 The stationary stochastic process

Stationarity in the strict¹ sense is defined as a series, whose joint and conditional distribution are both invariant with respect to displacement in time, i.e.,

 $P(Z_t,...,Z_{t+k}) = P(Z_{t+m},...,Z_{t+k+m})$

 $^{^1}$ It is possible for the mean variance and covariance of the series to be stationary, but not for the joint probability distributions. If the JPD are stationary, we term the series strict stationary.

or $P(Z_t) = P(Z_{t+m})$ for any t, k, m. If the series has to be stationary their mean, variance and covariance should also be stationary. For our purpose *weak stationarity* (" second-order stationarity") is defined as, a series where the mean is constant and the autocovariance function depends only on the time difference k = t-s, i.e.,

$$\mu_t = E[Z_t] = \mu = \text{const. and}$$

$$\gamma_{t,s} = \text{Cov} (Z_t, Z_s) = \gamma_{t-s} = \gamma_k, \quad k = t - s, \text{ it follows than}$$
$$\tau_k = \text{Cov}(Z_t, Z_{t+k}) = \text{E} [(Z_t - \mu) (Z_{t+k} - \mu)], \text{ such as}$$
$$\text{var}(Z_t) = \gamma_0 < \infty$$

3.3 The autocorrelation function of the stationary process

The autocorrelation function, which is standardized because the autocovariance depends on the unit of measurement, provides a measure of how much interdependence or correlation there is between neighboring data points in the series Z_{t} . The ACF is defined with k lags as follow :

$$\rho_k = \frac{\text{Cov}(Z_t, Z_{t+k})}{\text{Var}(Z_t)}$$

$$=\frac{\tau_k}{\tau_0}$$

We now also provide the well known properties of the autocorrelation function (ACF) as follows:

1)
$$\rho_0 = 1$$
 and $\rho_k = 0$ for $k > 0$

2)
$$\rho_k = \rho_{-k}$$

3) The autocorrelation matrix P_n of a stationary process Z_t , t = 1, 2, ..., N is as follows:

$$P_{n} = \begin{pmatrix} 1 & \rho_{1} & \rho_{2} & \rho_{N-1} \\ \rho_{1} & 1 & \rho_{1} & \rho_{N-2} \\ \rho_{2} & 1 & \rho_{N-3} \\ & & 1 \\ \rho_{N-1} \rho_{N-2} & 1 \end{pmatrix}$$

The matrix is positive definite, i.e. all principal minors are greater than zero. For N = 2, we show

$$\begin{vmatrix} 1 & \rho \\ \\ \\ \rho & 1 \end{vmatrix} > 0 \longrightarrow 1 - \rho_1^2 > 0$$

hence $-1 < \rho < 1$, similarly for higher N's the positiveness can be shown.

4) A stationary stochastic process Z_t with multivariate normal distribution is completely characterized by its mean μ and its variance and autocorrelation function.

3.4 The "white noise" process

A stochastic process Z_t , which can be described as a linear stochastic process, if each observation Z_t is expressed in the form

$$Z_t = \mu + u_t \Psi_0 + \Psi_1 u_{t-1} + \Psi_2 u_{t-2} + \dots$$

where μ and the Ψ_i are fixed parameters and the time series $(...,u_{t-1}, u_t,...)$ is a sequence of *identically* and *independently* distributed random disturbances with mean zero and variance σ_u^2 , is referred to as white noise.

For the stationarity conditions the mean and the variance-covariance matrix of the process must exists and be invariant with respect to time.

Mean:
$$E(Z_t) = \mu + E(u_t + \Psi_1 u_{t-1} +)$$

$$\sum_{i=0}^{\infty} \Psi_i = k$$

where $\Psi_0 = 1$ and k = some finite number. According to this the summation $\Sigma \Psi_i$ has to converge (For proof see Box–Jenkins 1976, p.80–82), then the mean of the process is

$$E(Z_{t}) = \mu$$

With $\mu = 0$ we can derive the variance and covariance as follows: (see also Nelson 1973, p.31-32)

Variance :
$$\gamma_0 = \sigma_u^2 \sum_{i=0}^{\infty} \Psi_i^2$$

Covariance :
$$\gamma_k = E(Z_t, Z_{t+k}) = \sigma_u^2 \sum_{i=0}^{\infty} \Psi_i \Psi_{i+k}$$

We see neither the variance nor does the covariance depend on t, a requirement of stationarity.

3.5 The linear filter model

The linear model we further discuss is based on the idea, Yule(1927), that a time series in which the successive observations are correlated to each other, can be described as generated from a series of independent "Schocks" e_t . These schocks are random drawings from a fixed distribution usually assumed as normal with mean $E(e_t) = 0$ and variance σ_e^2 , where e_t is further called "white noise" process.

The white noise process e_t a weighted sum of previous values will be transformed with a linear filter



as it becomes

$$Z_{t} = \mu + e_{t} + \psi_{1} e_{t-1} + \psi_{2} e_{t-2} + \dots$$

with the " backshift operator " defined as $B^m Z_t = Z_{t-m}$ the equation can be written as

(16)
$$Z_t = \mu + (1 + \psi_1 B + \psi_2 B^2 +) e_t$$

 $= \mu + \psi (B)e_{t}$

where the polynomial is the following :

$$\psi(B) = 1 + \psi_1 B + \psi_2 B^2 + \dots$$

and this linear operator transforms e_t into Z_t and is called the " transfer function " of the filter. Further , if the process has to be stationary the weights ψ_i must fulfill some conditions, i.e If the sequence is infinite and convergent, the filter is said to be stable and the process Z_t is stationary. (see also Box–Jenkins 1976, p.9–12)

3.6 The autoregressive process

A stochastic process (Z_t) is defined as autoregressive process of order p, shortly AR(P), if the following relationship can be described,

(17)
$$Z_t = \phi_1 Z_{t-1} + \dots + \phi_p Z_{t-p} + \delta + \varepsilon_t$$

where ε_t is a white noise process. In the above equation we can see that the explanatory variables are just the lagged or past values of the dependent variable. In the backshift form the equation can be written as

(18)
$$(1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p) Z_t = \delta + \varepsilon_t$$

and in the short form

$$\phi(B) Z_t = \delta + \varepsilon_t$$

$$Z_{t} = \phi^{-1}(B) \varepsilon_{t} = \varepsilon_{t} + \Psi_{1} \varepsilon_{t-1} + \Psi_{2} \varepsilon_{t-2} + \dots = \Psi(B) \varepsilon_{t}$$

Stationarity condition :

The stationarity of the following equation

$$\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p = 0,$$

i.e., instead of $\phi(B) = 0$ we mean $\phi(Z)$.

is achieved, if the roots of the characteristic equation lie outside the unit circle, i.e. | B | = 1. Further, each stationary process AR(P) can also be expressed as MA(∞) Z_t = $\varepsilon_t + \psi_1 \varepsilon_{t-1} +$, if the stationarity assumption is valid.(see Box and Jenkins 1976, p.53–54)

Parameters of AR(P) :

If the autoregressive process is stationary, then its mean μ must be invariant with respect to time; i.e., $E(Z_t) = E(Z_{t-1}) = E(Z_{t-2}) = = \mu$. The mean is given by

$$\mu = \phi_1 \ \mu + \phi_2 \ \mu + \dots + \phi_p \ \mu + \delta$$

or

Mean:
$$E(Z_t) = \frac{\delta}{1 - \phi_1 - \dots - \phi_p} = \mu$$

Autocovariance and Autocorrelation function¹:

Multiplying the eq.(17) with Z_{t-k} ($\delta = 0$) and taking expected values, we get for the autocovariance the following difference equation:

(19a)
$$\tau_{k} = \phi_{1} \tau_{k-1} + \phi_{2} \tau_{k-2} + \dots + \phi_{p} \tau_{k-p} \text{ for } k > 0$$

and

(19b)
$$\tau_0 = \phi_1 \tau_{-1} + \phi_2 \tau_{-2} + \dots + \phi_p \tau_{-p} + \sigma_{\varepsilon}^2$$

So, if we divide the eq.(19a) by τ_0 we get a linear difference equation for the autocorrelations.

(20)
$$\rho_k = \phi_1 \rho_{k-1} + \phi_2 \rho_{k-2} + \dots + \phi_p \rho_{k-p} \text{ for } k > 0$$

For k = 1, 2, ..., p, we get a system of p linear difference equations known as Yule–Walker equations.

So, if we divide eq. (19b) by τ_0 we get the variance of AR(p)- process:

(21)
$$\operatorname{Var}(\mathbf{Z}_{t}) = \tau_{0} = \frac{\sigma_{\varepsilon}^{2}}{1 - \rho_{1}\phi_{1} - \dots - \rho_{p}\phi_{p}}$$

¹ Partial autocorrelation function, which is used for the specification of the pure autoregresive models (see Nelson 1973, p. 82–83 and Box–Jenkins 1976, p. 64–65)

3.6.1 The autoregressive process of first order

The autoregressive model of the first order with $\delta = 0$ can be described as follow:

(22)
$$Z_{t} = \phi_{1} Z_{t-1} + \varepsilon_{t} \text{ or}$$
$$(1 - \phi_{1} B) Z_{t} = \varepsilon_{t}$$
$$Z_{t} = \frac{1}{(1 - \phi_{1} B)} \varepsilon_{t}$$

For the stationarity of the process the root (ϕ^{-1}) of the characteristic equation $(1 - \phi_1 B) = 0$ must lie outside the unit circle |B| = 1. i.e., $-1 < \phi < 1$.

Parameters :

It follows that the mean, variance and covariance of the AR(1) process are as: (see Pindyck and Rubinfeld 1981, p.520–521)

Mean:
$$E(Z_t) = \frac{\delta}{1 - \phi_1}$$

and now

$$\gamma_0 = \mathbb{E} \left[\left(\phi_1 \, Z_{t-1} + \varepsilon_t \right)^2 \right]$$

Using the eq. (21) the variance of the AR(1) is as follows:

Variance:
$$=\frac{\sigma_{\epsilon}^2}{1-\phi_1^2}$$

The covariance of the Z_t about its mean can be calculated as

$$\gamma_1 = \mathbb{E} \left[\mathbb{Z}_{t-1}(\phi_1 \mathbb{Z}_{t-1} + \varepsilon_t) \right] = \phi_1 \gamma_0 = \frac{\phi_1 \sigma_{\varepsilon}^2}{1 - \phi_1^2}$$

and for a k-lag displacement

$$\gamma_{\mathbf{k}} = \phi_1^{\mathbf{k}} \gamma_0 = \frac{\phi_1^{\mathbf{k}} \sigma_{\varepsilon}^2}{1 - \phi_1^2}$$

Autocorrelation function : From the eq.(20), the autocorrelation function satisfies the first-order difference equation $\rho_k = \phi_1 \rho_{k-1} \ k > 0$ which, with $\rho_0 = 1$, has the solution

$$\rho_k = \varphi_1^k \quad \text{ for } k > 0.$$

3.6.2 The autoregressive process of second order

The second order model can be written as follows

 $Z_{t} = \phi_{1} Z_{t-1} + \phi_{2} Z_{t-2} + \varepsilon_{t} \text{ or in backshift form}$ $(1 - \phi_{1} B - \phi_{2} B^{2}) Z_{t} = \varepsilon_{t}$

For the stationarity conditions the roots of the characteristic equation

 $(1 - \varphi_1 B - \varphi_2 B^2) = 0$ should lie outside the unit circle, i.e., |B| = 1 and where $\varphi_1 + \varphi_2 \le 1$, $\varphi_2 - \varphi_1 < 1$ and $|\varphi_2| < 1$.

Parameters :

The mean and variance of the AR(2) Process is as follows :



Autocorrelation function : Again from the eq.(20), the autocorrelation function satisfies the second order difference equation

(23)
$$\rho_{k} = \phi_{1} \rho_{k-1} + \rho_{2} \rho_{k-2} \text{ for } k > 0$$

which, with $\rho_0 = 1$ and

$$\rho_{1} = \frac{\phi_{1}}{(1 - \phi_{2})}$$
$$\rho_{2} = \frac{\phi_{1}^{2}}{(1 - \phi_{2}) + \phi_{2}}$$

autocorrelation for k > 2 can be recursively calculated from the eq.(23).
3.7 The moving average process

A stochastic process (Z_t) is defined as MA-process of order q, MA(q)-process, if it can be described as one, in which the current value of the series Z_t is a linear function of the current and previous errors or shocks, ε_t , can be written in the following form

$$Z_{t} = \mu + \varepsilon_{t} - \Theta_{1} \varepsilon_{t-1} - \dots - \Theta_{q} \varepsilon_{t-q}$$

Each observation Z_t is generated by a weighted average of random disturbances going back q periods and are white noise process with zero mean. The above equation can be written in backshift form as follow

$$Z_t = \mu + (1 - \Theta_1 B - \dots - \Theta_q B^q) \varepsilon_t$$

$$Z_t = \mu + \Theta (B) \varepsilon_t$$

A MA(q)-process with $q < \infty$ is always stationary because ψ (B) = Θ (B) possesses finite terms and it always converges. Further, a moving average process can be written as an infinite AR process, if the roots are outside the unit circle. If a moving average process meets this condition is called *invertible*.

Parameters of MA(q)-order :

As we see that $E(\varepsilon_{t}) = 0$ for all t, the mean of the process, which is also independent of time,

Mean :
$$E(Z_{\star}) = \mu$$

Let us now look at the variance, denoted by γ_0 , of the moving average process of order q:

Variance : $var(Z_t) = E[(Z_t - \mu)^2]$

$$= E \left(\varepsilon_{t}^{2} + \Theta_{1}^{2} \varepsilon_{t-1}^{2} + \dots + \Theta_{q}^{2} \varepsilon_{t-q}^{2} - 2 \Theta_{1} \varepsilon_{t} \varepsilon_{t-1} - \dots\right)$$
$$= \sigma_{\varepsilon}^{2} + \Theta_{1}^{2} \sigma_{\varepsilon}^{2} + \dots + \Theta_{q}^{2} \sigma_{\varepsilon}^{2}$$
$$= \sigma_{\varepsilon}^{2} \left(1 + \Theta_{1}^{2} + \dots + \Theta_{q}^{2}\right)$$

or

(24)
$$= \sigma_{\varepsilon}^2 \sum_{k=0}^{q} \Theta_k^2$$

Thus, if a MA of order q has to be stationary, than the Θ_i 's should become smaller as i becomes larger and sum $\Sigma \Theta_i^2$ converges.(see also Pindyck and Rubinfeld 1981, p.515-516)

The autocovariance of the MA process of order q is as follows

Covariance : $Cov(Z_t, Z_{t+k}) =$

(25)
$$\tau_{k} = \begin{cases} \sigma_{\epsilon}^{q-k} \sum_{k=0}^{q-k} \Theta_{k} \cdot \Theta_{q+k} & \text{for } k \le q, \Theta_{0} = -1 \\ 0 & \text{for } k > q \end{cases}$$

where $\Theta_0 = 1$. Than, the autocorrelations are

Autocorrelation :

(26)

$$=\frac{\tau_k}{\tau_0}$$

ρ_k

for k=1,2,...,q

 $= \begin{vmatrix} \frac{q-k}{\sum_{k=0}^{k} \Theta_k \Theta_{q+k}} & \text{for } k \\ \frac{q}{\sum_{k=0}^{q} \Theta_k^2} & \text{for } k \\ 0 & \text{for } k > q. \end{vmatrix}$ (see Judge, Grifith, Lee, Luetkepohl (1988) , Chapt. 16)

3.7.1 The moving average process of first order MA(1)

The moving average process of first order with $\mu = 0$ can be described as:

$$Z_t = \varepsilon_t - \Theta_1 \varepsilon_{t-1}$$

and in backshift form

$$Z_{t} = (1 - \Theta_{1}B)\varepsilon_{t}$$

A MA(1) process is always stationary and invertible, if $\mid \Theta_1 \mid < 1$.

Parameters :

From the conditions of white noise in section 3.4, we see that the mean is zero and the variance constant such that

$$E(Z_t) = E(\varepsilon_t - \Theta_1 \varepsilon_{t-1}) = E\varepsilon_t - \Theta_1 \varepsilon_{t-1} = 0$$

Similarly, the variance is as follows:

$$\begin{split} & \mathbb{E}[\left(\varepsilon_{t} - \Theta_{1}\varepsilon_{t-1}\right)^{2}] = \mathbb{E}\left(\varepsilon_{t}^{2} - 2\Theta_{1}\varepsilon_{t-1}\varepsilon_{t} + \Theta_{1}^{2}\varepsilon_{t-1}^{2}\right) \\ & = (1 + \Theta_{1}^{2})\sigma_{\varepsilon}^{2} \end{split}$$

Further, we see that the covariance is also constant :

$$Cov(Z_t, Z_{t-1}) = E[(\varepsilon_t - \Theta_1 \varepsilon_{t-1}) (\varepsilon_{t-1} - \Theta_1 \varepsilon_{t-2})]$$
$$= E(-\Theta_1 \varepsilon_{t-1}^2)$$
$$= -\Theta_1 \sigma_{\varepsilon}^2$$

At zero and first lag, we calculated the autocovariance. Similarly, at the second lag the autocovariance is obtained as:

Cov (Z_t, Z_{t-2}) = E [(
$$\varepsilon_t - \Theta_1 \varepsilon_{t-1}$$
) ($\varepsilon_{t-2} - \Theta_1 \varepsilon_{t-3}$)]
= 0

and it can also be shown for $k \ge 2$ that autocovariance is zero. Now, the autocorrelation is defined as:

Autocorrelation: $\rho_k = \frac{\tau_k}{\tau_0}$

$$= \begin{vmatrix} -\Theta_1 \\ 1 + \Theta_1^2 \\ 0 \\ k \ge 2 \end{vmatrix}$$

3.7.2 The moving average process of second order MA(2) The moving average process of the second order can be written as:

$$Z_t = \varepsilon_t - \Theta_1 \varepsilon_{t-1} - \Theta_2 \varepsilon_{t-1}$$

and in the backshift form

$$Z_t = (1 - \Theta_1 B - \Theta_2 B^2) \varepsilon_t$$

This process is invertible, if the roots of the characteristic equation $(1 - \Theta_1 B - \Theta_2 B^2 = 0)$ lie outside the unit circle and |B| = 1, and in addition to that the following conditions can be derived, i.e., $\Theta_1 + \Theta_2 < 1$, $\Theta_2 - \Theta_1 < 1$ and $|\Theta_2| < 1$; we see that these are analogous to the AR(2) process.

Parameters :

Mean : E(t) = 0

The variance of the process is given by :

Variance : $Var(Z_t) = (1 + \Theta_1^2 + \Theta_2^2) \sigma_{\varepsilon}^2$

 $\label{eq:covariance} Covariance: Cov(\tau_2) = -\,\Theta_2 \,\,\sigma_2^2 \quad \text{ and } \tau_k = 0 \ \text{ for } k > 2$

Autocorrelation : $\rho_1 = \frac{-\Theta_1 (1-\Theta_2)}{1+\Theta_1^2+\Theta_2^2}$

$$\rho_2 = \frac{-\Theta_2}{1 + \Theta_1^2 + \Theta_2^2}$$

$$\rho_k = 0$$
 for $k > 2$

3.8 The mixed autoregressive-moving average process ARMA(p,q)

If a stationary process can not be modeled as purely AR or MA process then we require an extention to these models. The extension would be to models which have both AR and MA terms and are called autoregressive—moving average of order (p,q). We define this process as ARMA(p,q) and represent it as:

(27)
$$Z_{t} = \phi_{1} Z_{t-1} + \dots + Z_{t-p} + \delta + \varepsilon_{t} - \Theta_{1} \varepsilon_{t-1} - \dots - \Theta_{q} \varepsilon_{t-q}$$
$$(1 - \phi_{1} B - \dots - \phi_{p} B^{p}) Z_{t} = (1 - \Theta_{1} B - \dots - \Theta_{q} B^{q}) \varepsilon_{t} + \delta$$
$$\phi (B) Z_{t} = \Theta (B) \varepsilon_{t} + \delta$$

The stationarity of ARMA-process is analogous to the AR process, i.e., the roots of the characteristic equation ϕ (B) = 0 lie outside the unit circle | B | = 1. Further, if stationarity is presumed than the ARMA(p,q) process can be transformed as MA(∞) and AR(∞). For the invertibility of moving average part the roots must lie outside the unit circle. The distinctive pattern of the ARMA models is its *parismony*, i.e., the higher order MA and AR processes can be approximated with the less parameterized ARMA process (see Box-Jenkins 1976, p. 17–18, 302, 340).

Parameters :

The mean of the ARMA Process is similar to that for the AR process and can be given as:

Mean :
$$E(Z_t) = \frac{\delta}{1 - \phi_1 - \dots - \phi_p} = \mu$$

In general the variance, covariance, and autocorrelations of ARMA(p,q) are solutions to difference equations, but we get the autocovariance function, if we multiply the eq.(27) with Z_{t-k} :

(28)
$$\gamma_{k} = \phi_{1} \gamma_{k-1} + \dots + \phi_{p} \gamma_{k-p} + E [Z_{t-k}\varepsilon_{t}] - \Theta_{1} E [Z_{t-k}\varepsilon_{t-1}] - \dots - \Theta_{q} E [Z_{t-k}\varepsilon_{t-q}]$$

So, with k=0 we get the Variance :

(29)
$$\tau_0 = \phi_1 \gamma_1 + \dots + \phi_p \gamma_p + \sigma_p^2 - \Theta_1 E \left[Z_{t-k} \varepsilon_{t-1} \right] - \dots - E \left[Z_t \varepsilon_{t-q} \right]$$

As we know that E[$Z_{t-k} \epsilon_{t-j}$] is zero for k > j, then the autocovariance for k > q has the form

(30)
$$\gamma_{k} = \phi_{1} \gamma_{k-1} + \phi_{2} \gamma_{k-2} + \dots + \phi_{p} \gamma_{k-p} \text{ for } k > q$$

If we divide eq.(30) by γ_0 we get the autocorrelation function as :

 $\rho_k = \varphi_1 \ \rho_{k-1} + \varphi_2 \ \rho_{k-2} + \dots + \varphi_p \ \rho_{k-p} \quad \text{ for } k > q$

3.8.1 The first order ARMA process

The first order autoregressive-moving average model can be written as:

(31)
$$Z_{t} = \delta + \phi_{1} Z_{t-1} + \varepsilon_{t} - \Theta_{1} \varepsilon_{t-1}$$

or

$$(1 - \phi_1 B)Z_t = (1 - \Theta_1 B) \varepsilon_t$$

The mean of the ARMA(1,1) process is given by

$$E(Z_t) = \phi_1 E(Z_{t-1}) + \delta + E(\varepsilon_t) - \Theta_1 E(\Theta_t \delta_1)$$
$$= \frac{\delta}{1 - \phi_1}$$

the same as for the AR(1) process.

The variance can be calculated by squaring the right-hand side of the eq.(31) and taking expectations :

$$\operatorname{Var}(Z_{t}) = \operatorname{E}(Z_{t}^{2}) = \operatorname{E}\left[\left(\phi_{1} \ Z_{t-1} + \varepsilon_{t} - \Theta_{1} \ \varepsilon_{t-1}\right)^{2}\right]$$
$$= \phi_{1}^{2} (\operatorname{E} Z_{t-1}^{2}) + \sigma_{\varepsilon}^{2} + \Theta_{1}^{2} \ \sigma_{\varepsilon}^{2} - 2 \ \Theta_{1} \ \phi_{1} \ \operatorname{E}(Z_{t-1} \varepsilon_{t-1})$$

We know that $E(Z_{t-1} \epsilon_{t-1}) = \sigma_{\epsilon}^2$, from this it follows:

Variance :
$$\tau_0 = \frac{(1 + \Theta_1^2 - 2 \phi_1 \Theta_1)}{1 - \phi_1^2} * \sigma_{\epsilon}^2$$

The Autocovariance at lag 1 can similarly be calculated as

$$\begin{split} \gamma_1 &= \mathrm{E}(\mathrm{Z}_t \, \mathrm{Z}_{t-1}) = \mathrm{E} \, (\varphi_1 \, \mathrm{Z}_{t-1}^2 + \varepsilon_t \, \mathrm{Z}_{t-1} - \Theta_1 \, \varepsilon_{t-1} \mathrm{Z}_{t-1}) \\ &= \varphi_1 \, \gamma_0 - \Theta_1 \, \sigma_\epsilon^2 \end{split}$$

since $\mathrm{E}(\boldsymbol{\epsilon}_t \; \boldsymbol{Z}_{t-1}) = 0$ and for γ_0 and rearranging terms, we obtain

Covariance:
$$\tau_1 = \frac{(1 - \phi_1 \ \Theta_1) \ (\phi_1 - \Theta_1)}{1 - \phi_1^2} \ \sigma_{\epsilon}^2$$

Now, the Autocorrelation we get is as follows:

Autocorrelation :

$$\rho_1 = \frac{\tau_1}{\tau_0}$$

$$= \frac{(1 - \phi_1 \ \Theta_1) \ (\phi_1 - \Theta_1)}{1 + \Theta_1^2 - 2 \ \phi_1 \ \Theta_1}$$

Thus for displacement k greater than 1

$$\rho_k = \phi_1 \rho_{k-1} \text{ for } k \ge 2$$

3.8.2 Invertibility of first order ARMA

In this section we will transform the ARMA(1,1) into an infinite AR (∞) form in order to test its lag structure (see Nerlove(1972) for discussion about lags in economic behavior). We already know the invertibility property of a ARMA model. Now let the ARMA(1,1) be as:

(32)
$$Z_{t} = \phi_{1} Z_{t-1} + \delta + \varepsilon_{t} - \Theta_{1} \varepsilon_{t-1}$$

then $\varepsilon_t = Z_t - \phi_1 Z_{t-1} - \delta + \Theta_1 \varepsilon_{t-1}$

now $\varepsilon_{t-1} = Z_{t-1} - \phi_1 Z_{t-2} - \delta + \Theta_1 \varepsilon_{t-2}$

We now put ε_{t-1} in the eq.(32) and the equation becomes as follows:

$$Z_t = \varepsilon_t + (\delta + \Theta_1 \delta) + (\phi_1 - \Theta_1) Z_{t-1} + \phi_1 \Theta_1 Z_{t-2} - \Theta_1^2 Z_{t-2}$$

and with further substitutions of ε_{t-2} , ε_{t-3} and so on, we get an infinite form of AR(∞) as follows:

$$Z_{t} = (\phi_{1} - \Theta_{1}) Z_{t-1} + \Theta_{1}(\phi_{1} - \Theta_{1}) Z_{t-2} + \Theta_{1}^{2} (\phi_{1} - \Theta_{1})$$
$$Z_{t-3} + \dots + \frac{\delta}{1 - \Theta_{1}} + \varepsilon_{t}$$

If the invertibility conditions are to be fulfilled then the following expression

(33)
$$\Pi_{i} = \sum_{i=1}^{\infty} \Theta_{1}^{i-1} (\phi_{1} - \Theta_{1})$$

should converge and hence $|\Theta_1| < 1$.

3.8.3 The delta method

If an autoregressive approximation to ARMA(1,1) has to be obtained we truncate the autoregression where the coefficient becomes sufficiently small. In order to find where the coefficient actually has to be truncated, we calculate the asymptotic variance of Π_i by the delta method (see Bishop, Feinberg and Holland (1975)), since τ is a well-behaved function of the parameters β estimated by the maximum-likelihood method, the asymptotic variance is given by:

$$\operatorname{Var}(\tau) = \frac{\partial \tau}{\partial \beta} \quad \Omega \frac{\partial Y^{1}}{\partial \beta}$$

where Ω denotes the covariance matrix of β , and T denotes transpose.

Procedure :

Step 1: Transform the ARMA(1,1) into the following expression (see section 3.8.2, p.37)

$$\mathbf{Z}_{t} = \boldsymbol{\Theta}_{1}^{i-1}(\boldsymbol{\varphi}_{1} - \boldsymbol{\Theta}_{1})$$

Derive Z_i with respect to Θ_1 as

$$\frac{\partial \ Z_i}{\partial \ \Theta_1} = (\phi_1 - \Theta_1) \ (i{-}1) \ . \ \Theta_1^{i-2} + \Theta_1^{i-1} \ ({-}1)$$

and then with respect to ϕ_1

$$\frac{\partial Z_i}{\partial \phi_1} = \Theta_1^{i-1}$$

Step 2: calculate the variance of the eq.(33) as follows:

$$\begin{bmatrix} \frac{\partial}{\partial} & z_{i} \\ \frac{\partial}{\partial} & \Theta_{1} \end{bmatrix}^{*} \frac{\partial}{\partial} & z_{i} \\ \frac{\partial}{\partial} & z_{i} \end{bmatrix}^{T} \begin{bmatrix} \Omega_{11} & \Omega_{12} \\ \Omega_{12} & \Omega_{22} \end{bmatrix}^{T} \begin{bmatrix} \frac{\partial}{\partial} & z_{i} \\ \frac{\partial}{\partial} & \Theta_{1} \\ \frac{\partial}{\partial} & \varphi_{1} \\ \frac{\partial}{\partial} & \varphi_{1} \\ \frac{\partial}{\partial} & \varphi_{1} \\ \frac{\partial}{\partial} & \varphi_{1} \end{bmatrix}^{T}$$

where

$$\begin{bmatrix} \Omega & \Omega \\ \Omega^{11} & \Omega^{12} \\ 12 & 22 \end{bmatrix}$$
 is a Variance – Covariance matrix of Θ and ϕ .

3.8.4 The non-stationary process

Many empirical time series encountered in practice can be described as **non-stationary** processes, such that the characteristics of the underlying stochastic process changes over time. So we can then not use the models discussed so far in a straight forward manner. Often transformations¹ of the data will be necessary to induce stationarity. We construct models for non-stationary series which can be transformed into stationary series by differencing one or more times. We say that Z_t is homogeneous nonstationary of order d if

$$w_t = \nabla^d Z_t$$

is a stationary series. Here ∇ denotes differencing², i.e.,

$$\nabla Z_t = Z_t - Z_{t-1} \quad \nabla^2 Z_t = \nabla Z_t - \nabla Z_{t-1}$$
 and so forth.

Now, if we apply a difference filter to a nonstationary process as follows, consider a AR(1) process

$$Z_t = \phi_1 Z_{t-1} + \varepsilon_t$$

If ϕ_1 is less than 1, then the process is stationary. On the other hand, if ϕ_1 is greater than 1, then the behavior of the series will be explosive. For the $\phi = 1$ the equation becomes a random walk process. It is also homogeneous because the distribution of changes or differences in the process is unchanging, i.e., the time series of differences is stationary because the differences are just

$$Z_t - Z_{t-1} = \varepsilon_t$$
, known as random walk,

and the distribution of ε_t is fixed.

¹ to remove the non-stationarity in the variance the Box-Cox transformation is purposed (see Schlittgen and Streitberg 1984, p. 81f, 436)

 $^{^2}$ Plosser et.el.(1982) suggests that a comparison of the OLS- estimates from a presumably correctly specified regression equation with the estimators from the differenced form of the same model can provide important insights into the regression specification.

Let us define w_t to be the sequence of differences

$$\mathbf{w}_t = \mathbf{Z}_t - \mathbf{Z}_{t-1}$$

hen the general ARMA model can be written as

$$w_t = \phi_1 \ w_{t-1} + \dots + \phi_p \ w_{t-p} + \varepsilon_t - \Theta_1 \varepsilon_{t-1} - \dots - \Theta_q \ \varepsilon_{t-q}$$

So, if we replace w_t with $(Z_t - Z_{t-1})$, we see that the observed series Z_t is given by

$$Z_{t} = Z_{t-1} + \phi_{1} (Z_{t-1} - Z_{t-2}) + \dots + \phi_{p} (Z_{t-p} - Z_{t-p-1})$$
$$+ \varepsilon_{t} - \Theta_{1} \varepsilon_{t-1} - \dots - \Theta_{q} \varepsilon_{t-q}$$

So, from this equation we see that Z_t is just the sum of all past changes, i.e,

$$Z_t = w_t + w_{t-1} + w_{t-2} + \dots$$

Now, the Z_t is referred to as an integration of the w_t series, and the process as an integrated autoregressive – moving-average (ARIMA) process. The ARIMA(p,d,q) process has the form as follows:

$$(1 - \phi_1 B - ... - \phi_p B^p) (1 - B)^d = (1 - \Theta_1 B - ... - \Theta_q B^q) \varepsilon_t$$

where d is the order of differencing and ε_t as white noise process with mean equal zero. (see also Nelson (1973), p.57 and for application Harvey(1980)).

3.8.5 Estimation method

If a model is linear or it can be made linear through transformations, the OLS estimates can be obtained directly. But, if the model is non-linear, as the ARIMA model in general is, OLS can not be applied directly. The numerical solutions must then be obtained by means of an iterative algorithm. We describe the estimation method without going into mathematical details for ARMA shortly as follows : (For detailed explanation see Pindyck and Rubinfeld 1981, p. 539-547, Dent and Min(1978) did a simulation study with a different estimation method. For the small sample properties of lag estimators, see, Morrison(1970), Maeshiro(1980)). Let us write the model from section 3.8.1 as

$$\varepsilon_{t} = \Theta^{-1}(B) \phi(B) Z_{t}$$

we see Θ is non-linear and OLS can not be *directly* applied.

The objective is to find the values of ϕ and Θ that minimize the sum of squared errors, i.e.

$$S(\phi,\Theta) = \sum_{t=1}^{T} [\varepsilon_t \mid \phi, \Theta, w]^2$$

where ε_t are conditional on ϕ , Θ , w, because we need initial values to start the iteration: Step 1 :

The non-linear estimation process uses the first two terms in a taylor series expansion to linearize the equation around an initial guess for ϕ and Θ .

Step 2:

A linear regression is applied on this linearized equation, and OLS-parameters are obtained; if the process does not converge these parameters values are used for the next iteration and so on. This process is repeated until convergence occurs and we obtain, at the final stage, linear estimates.

4. Identification of time series

4.1 The basic idea

If a time series is not stationary, as is quite often the case with economic time series, then the time series is differenced in order to achieve stationarity. The usual autocorrelation, partial autocorrelation functions and their corrolograms are used for determining the orders of the respective models. While the Box- Jenkins approach is useful in specifying purely autoregressive (q = 0) or purely moving average (p = 0) models, it is difficult to determine the values of p and q for mixed models. Tsay and Tiao (1984) provides a method ESACF (Extended Sample Autocorrelation Function), which we want to discuss in this section, where the appropriate order of the ARMA and ARIMA process can be found without differencing the required time series.

In contrast to the Box – Jenkins procedure, we can derive, firstly, the consistent LS – Estimates of autoregressive parameter with the iterative estimation and secondly, with these parameters the ESACF can be found. Jeon and Park (1986) found a weakness of the ESACF, i.e., that ambiguity can be caused by the elements which are in the triangle but marginally larger than the two standard deviation values. They proposed another procedure to avoid this draw back, a vector sample autocorrelation function (VSACF). Gray, Kelly and McIntire (1978) proposed an alternative technique R-S-Array to the Box-Jenkins approach of ARMA(p, q) model identification based on S-array, but this procedure is quite difficult and complex for practical applications and further their statistical properties are unknown. A more simpler criterion known as the corner method is provided by Beguin, Gourieroux and Monfort (1980). The interesting feature of this criterion is that it allows for statistical testing procedures. A further discussion about the corner method can be seen in Gooijer and Heuts (1981).(For another method of identification and estimation with charts, see Stralkowski and Wu(1974)).

Woodward and Gray (1981) discuss in their paper the concept of the generalized partial autocorrelation function (GPAC), which is the extension of the partial autocorrelation function and show the relationship between the S-array and the Box-Jenkins method of ARMA identification. Gooijer, Abraham, Gould and Robinson (1985) briefly discuss in their survey article several of the most important order determination methods used in time series analysis.

4.2 Extended sample autocorrelation function

Let ARMA (p,q) be the model for a univariate time series Z_t in the form

(34)
$$\phi(B) Z_{t} = \Theta(B). a_{t}$$

where B is a backshift operator B $Z_t = Z_{t-1}$ and a_t Gaussion white noise process with zero mean and σ_a^2 variance

and where $\phi(B) Z_t$ is the autoregressive term and $\Theta(B) a_t$ is the moving average term

 ϕ (B) = 1 - ϕ_1 B -.... - ϕ_p B ^p is further divided into two portions,

U (B) and $\varphi(B)$ as now

 ϕ (B) = U (B) . ϕ (B) with the following polynomials in

 $U(B) = 1 - U_1 B - \dots U_d B^d$

 $\phi \left(B \right)$ = 1 – ϕ_1 B –..... $\phi_{p \ -d}$ B $^{p \ -d}$ with the following conditions

1) If the roots of U(B) are on the unit circle, so is the U(B) the non-stationary part of φ(B).
 2) If the roots of φ (B) lie outside the unit circle, so is φ (B) the stationary part of φ (B).
 3) φ (B) and Θ (B) have no common factors.

Under the conditions (1) and (2) the following is required

if U (B) = 1, then it is the autoregressive part ϕ (B) purely stationary

if $\phi(B) = 1$, then is the autoregressive part $\phi(B)$ non-stationary.

4.3 Iterative estimation

Starting point :

Suppose n observation are available from the ARMA (p,q) process in the following form

(35)
$$Z_{t} = \sum_{l=1}^{p} \phi_{l} Z_{t-1} - \sum_{j=1}^{q} \Theta_{j} a_{t-j} + a_{t}$$

The purpose here is to find the consistent LS - estimator

Iterations:

Suppose that Z_t is a AR (p) model then

We consider the OLS - Estimates

-----> means convergence in the probabality.

If the process is either a pure AR(P) that is (q = 0) process or is a pure non-stationary ARMA(p,q) process that is $\varphi(B) = 1$.

For other models the OLS-Estimation is inconsistent and in this case we proceed to the

1. Iteration step

We consider the estimated residuals

$$\hat{e}_{p,t}^{(0)} = Z_t - \sum_{l=1}^{p} \hat{\phi}_{l(p)}^{(0)} Z_{t-l}$$

which are not white noise even for large n, the lagged values $e_{p,t-j}^{(0)}$, j > 0, will contain some information about the process Z_t and define the 1. Iterative AR(P) regression

(37)
$$Z_{t} = \sum_{l=1}^{p} \phi_{l(p)}^{(1)} Z_{t-l} + \beta_{1 p}^{(1)} \hat{e}_{p,t-1} + e_{p,t}^{(1)}$$

(1)where $e_{p,t}^{(*)}$ denotes the corresponding error term and superscript (1) means the first iterated regression.

We calculate the OLS-estimates $\hat{\phi}_{1(p)}^{(1)}$, $\hat{\beta}_{l(p)}^{(1)}$ and get the following results.

$$\oint_{l(p)}^{(1)} \frac{p}{l(p)} \rightarrow \oint_{l} l = 1, \dots, p$$

if $q \le 1$, i.e., AR(P) or ARMA(P,1) or $\varphi(B) = 1$, i.e., pure non-stationary For other models the Estimator $\hat{\phi}^{(1)}$ is inconsistent, and in this case we proceed to the 2nd 1(p)

Iteration.

2. Iteration

Let

l(p)

$$\hat{e}_{p,t}^{(1)} = Z_t - \sum_{l=1}^{p} \hat{\phi}_{l(p)}^{(1)} Z_{t-l} - \hat{\beta}_{l(p)} \hat{e}_{p t-1}^{(0)}$$

and define the 2.AR(p) regression as

(38)
$$Z_{t} = \sum_{l=1}^{p} \phi_{l(p)}^{(2)} Z_{t-l} + \beta_{l(p)}^{(2)} e_{p,t-1}^{(1)} + \beta_{2(p)}^{(2)} e_{p,t-2}^{(0)} + e_{p,t}^{(2)}$$

where t = p + 3,, n and $e_{p,t}^{(2)}$ denotes error term. We consider the OLS-estimates

$$\hat{\phi}_{1(p)}^{(2)}, \hat{\beta}_{1(p)}^{(2)}, \hat{\beta}_{2(p)}^{(2)} \text{ and get the following results}$$

$$\hat{\phi}_{1(p)}^{(2)} \xrightarrow{p}_{1(p)} \phi_{1}^{(2)} = 1, \dots, p$$

If q < 2 or $\varphi(B) = 1$, otherwise the estimator is inconsistent, the jth iterated AR(k) regression 'is defined as

(39)
$$Z_{t} = \sum_{l=1}^{k} \phi_{l(k)}^{(j)} Z_{t-l} + \sum_{i=1}^{j} \beta_{i(k)}^{(j)} e_{k,t-j}^{(j-i)} + e_{k,t}^{(j)}$$

where t = k + j + 1,...,n

j = 0,....

k = 1,2,.....

and now

(40)
$$\hat{e}_{k,t}^{(i)} = Z_t - \sum_{l=1}^k \hat{\phi}_{lk} Z_{t-l} - \sum_{k=1}^i \hat{\beta}_{h(k)}^{(i)} \hat{e}_{k,t-h}^{(i-h)}$$

are the estimated residuals from the ith iterated AR(k) regression and

 $\hat{\phi}_{l(k)}^{(i)}$'s and $\hat{\beta}_{h(k)}^{(i)}$'s the corresponding estimates.

4.4 Recursion

It will be shown now that the estimates $\oint_{l(k)}^{(j)} can be recursively computed from the OLS estimates. If we give k, j and the index <math>l = 1, ..., k$ some values than the recursion can be started as follows.

For j = 0 the coefficient $\oint_{l(k)}^{(0)}$ are obtained from the OLS estimation directly.

Now the recursion step for j = 1 becomes

$$\hat{\phi}_{l(k)}^{(1)} = \hat{\phi}_{l(k+1)}^{(0)} - \frac{\hat{\phi}_{l(k)}^{(0)} * \hat{\phi}_{l(k)}^{(0)}}{\frac{l-1(k) + 1}{k} + 1} + \frac{\hat{\phi}_{l(k)}^{(0)}}{\hat{\phi}_{l(k)}^{(0)}}$$

where $\hat{\Phi}_{0(k)}^{(0)} = -1$, so we can also derive similarly the recursion steps for j=2 and so on, Now 0(k)

the jth recursion step is as follows

(41)
$$\hat{\phi}_{l(k)}^{(j)} = \hat{\phi}_{l(k+1)}^{(j-1)} - \frac{\hat{\phi}_{l(j-1)}^{(j-1)} * \hat{\phi}_{l(j-1)}^{(j-1)}}{\frac{1-1 \quad (k) \qquad k+1 \quad (k+1)}{\hat{\phi}_{l(j-1)}}}$$

where $\oint_{0(k)}^{j-1} = -1$, $l = 1, \dots, k$ and k > 1, j > 1. It should be clear that at the begining of recursion the coefficient $\oint_{1(k+j)}^{(0)}$ must have been calculated previously.

ESACF (Extended Sample Autocorrelation Function)

We define now the ESCAF-function $r_{j(k)}$ for the numbers k,j, using the consistent estimates. Again we have a ARMA(p,q) model and

1. If p=0, then we have Z_t as MA(q) model and its SACF cuts off asymptotically at lag q, i.e.,

(42)
$$r_{j(0)} = 0 \text{ if } j > q \text{ and } p = 0 ,$$

where j = lag and q is order of the process, \doteq asymptotically equivalent in probability.

2. If p=1, then we have Z_t as ARMA(1,q) model, if a consistent estimate $\overline{\varphi}_1$ of φ_1 can be found, then $W_t = Z_t - \overline{\varphi}_1 Z_{t-1}$ will asymptotically follow a pure MA(q) model, and its SACF will have its property as in 1.

With the AR-iterations we get the following result

 $\phi_{1(1)}^{(j)} \xrightarrow{p} \phi_{1(1)} \rightarrow \phi_{1}$, $j \ge q$ and because of the preliminary results it follows that

the process $W_{1,t}^{(q)} = Z - \phi_{1(1)}^{(q)} Z$ is as a MA(q) model so that

 $r_{s}(W_{1,t}^{(q)}) \doteq 0$ for s > q we can now define the

1.ESACF of
$$Z_t$$
 as
(43) $r_{j(1)} = r_j (W_{1,t})$

where (1) means first ESACF and we can now see

 $r_{j(1)} = 0$ if j > q and p = 1 $r_{j(1)} = 0$ if j = q and p = 1 In general, for any non-negative integer k we define the kth ESACF of Z_t as

(44)
$$r_{j(k)} = r_j (W_{k,t}^{(j)})$$
 where

$$W_{k,t}^{(j)} = Z_t - \sum_{l=1}^{k} \hat{\phi}_{l(k)}^{(j)} Z_{t-l}$$
 and j = iterations, k = time series

If the true model is ARMA(p,q), we have that asymptotically $W_{p,t}^{(j)}$ follows an MA(q) model for $j \ge q$, so that

$$(45) r_{j(k)} \doteq 0 \text{ for } j > q \text{ and } k = p \\ r_{j(k)} = 0 \text{ for } j = q \text{ and } k = p$$

4.5 The asymptotic ESACF- tables

According to the asymptotic property of ESACF $r_{i(k)}$, which is given as

(46)
$$r_{j(k)} \stackrel{\text{\tiny \doteq}}{=} C (k-p, j-q) \text{ with } 0 \le j-q \le k-p$$
$$\stackrel{\text{\tiny \doteq}}{=} 0 \ j-q > k-p \ge 0$$

where C (k - p, j - q) is some non-zero constant or a continuous random variable bounded between -1 and 1.

With the help of this property we can identify the ARMA(p,q) model, i.e.,we arrange the $r_{j(k)}$ in a two-way table , such that the first row corresponds to the autocorrelation of the time series Z_t and the second row to the ESACF of the process $W_{1t}^{(j)}$ and so on.

So, we search from the tables for the vertex of asymptotic "zeros" values with the boundary lines $k = c_1 \ge 0$ and $j - k = c_2 \ge 0$ and then identify $p = c_1$ and $q = c_2$ as the order of the ARMA model.

We further approximate the asymptotic variance of the $r_{j(k's)}$ by using Bartlett's formula (see Nelson 1972,p.74). So for each value $r_{j(k)}$ we have a limit $S_{j(k)}$, so is $[r_{j(k)}] > 2 \times S_{j(k)}$, than we have "X" otherwise "0". So the $S_{j(k)}$ is given as follows:

(47)
$$S_{j(k)} = \frac{1}{\sqrt{T - K}} (1 + 2 \sum_{l=1}^{j-1} r_{j(k)}^{2})^{1/2} \text{ for } j > q .$$

			MA				
AR	0	1	2	3	4	5	
0	^r 1(0)	^r 2(0)	^r 3(0)	^r 4(0)	^r 5(0)	^r 6(0)	
1	r 1(1)	^r 2(1)	•	•		•	
2		•	•		.•	•	
3	•	•	•	^r j(k)	•		
4				•			
5		•	•	•			
				·····			
Indicator	r symbol tab	le	Ϋ́,				
Indicator	r symbol tab	le	МА				
<u>Indicator</u> AR	r symbol tab	le 1	MA 2	3	4	5	
AR 0	r symbol tab	1 X	MA 2 X	3 X	4 X	5 X	
AR 0 1	o X X X	le 1 X 0	MA 2 X 0	3 X 0	4 X 0	5 X 0	
AR 0 1 2	r symbol tab	le 1 X 0 X	MA 2 X 0 0	3 X 0 0	4 X 0 0	5 X 0 0	
AR 0 1 2 3	r symbol tab	le 1 X 0 X X X	MA 2 X 0 0 X	3 X 0 0 0	4 X 0 0 0	5 X 0 0 0	
AR 0 1 2 3 4	r symbol tab	le 1 X 0 X X X X	MA 2 X 0 0 X X X	3 X 0 0 0 0 X	4 X 0 0 0 0 0	5 x 0 0 0 0 0 0	

The ESACF- table

5. Model diagnostics

After the model has been identified and the parameters estimated the general diagnostic checks are then applied to the fitted models in order to see whether or not the model is correctly specified. The diagnostic checking process involves the following major steps.

5.1 Test applied to residuals

5.1.1 Portmanteau test

Instead of considering the autocorrelations individually, it is worth taking them as a whole. Suppose that we have K autocorrelations :

$$r_{k}(a), k = 1, 2, \dots, K$$

from any ARIMA(p,d,q) process, if the fitted model is appropriate a test can be made for their adequacy with the Box-Pierce (1970) Test-statistic:

$$Q = n \sum_{k=1}^{K} r (a)$$

and which is approximately distributed as χ^2 (k - p - q) degrees of freedom.

Ljung and Box (1978) suggests to use the modified Test-statistic. On the power of portmanteau statistics (see Davies, et.el.(1977), Davies and Newbold (1979), Godfrey(1979), Postkitt and Tremayne (1980)).

$$Q^* = n (n+2) \sum_{k=1}^{K} (n-k)^{-1} \hat{r}_k^2$$

because the mean of Q can be approximated with

$$E(Q) = \frac{m * n}{n + 2} \left[1 - \frac{m + 1}{2n}\right] - p - q$$

from this formula it is obvious that n must be large relative to m and that the Q is approximately $\chi^2(m-p-q)$ distributed.

Schlittingen and Streitberg (1984) suggests that doubt can be put on the validity of a ARMA(p,q), if one of the following phenomena is observed:

- the parameters are instable in the less parameterized model, i.e., the parameter estimation differs considerably if the model is extended.

- the new added parameters are significantly different from zero.

- the residual variance declines, if the model is extended.

5.1.2 Overfitting

To an identified model of the form ARIMA(p,d,q), another model with additive parameters can be added as an extension like ARIMA(p+p', d, Q+Q') and then estimated. After the model with additional parameters has been estimated its parameters should be statistically insignificant. If we apply this procedure serious difficulties¹ in the estimation can arise. If a model is fitted which contains a redudant factor, consequently it leads to instability of the parameters

$$(1 - \alpha B) \phi(B) W_{\star} = (1 - \alpha B) \Theta(B) a_{\star}$$

i.e., the model should not take the above form, the caution is not to add "MA" and "AR" parameters at the same time.

¹

Larimore and Mehra (1985) show empirically and mathematically how overfitting in time series analysis leads to an increase in forecast errors.

EMPIRICAL PART:

6. Introduction

a) Section 6.1 describes the data and the definitions of profit measures and reports the descriptive statistics. It then explains the effect of trend and business cycle on the mean rate of return. Finally, the convergence process of some selected German firms is illustrated.

b) In section 7. the polynomials models from page 7 are applied to the German data alone to get initial insights of the POP- hypothesis. (The US results of these models are taken from Mueller(1983)). The results of these models are then compared across countries. Furthermore in this section the results of the partial adjustment model (PA-model) are reported for both countries and then the lagrange multiplier approach to testing for autocorrelation is also applied. Finally the results of the whole section are then summarized.

c) In sections 8. and 9. the results of the stochastic models for both countries are reported. The test of lag structure is evaluated. The unit root test is then applied to check the stationarity conditions on both samples. Finally the model selection procedure is applied to discriminate between the models.

d) Section 10. reports first the results of large sample example to see the operationality of this identification procedure. This procedure is then applied to both countries and the results for some selected firms from both countries are reported and finally summarized.

e) The final section 11. compares the results of the PA-model, and stochastic models of equivalent and complete time periods between two countries. The results of the industrial differences from stochastic models are compared and then finally the summary and conclusions are drawn.

6.1 Data description

For the purpose of comparing results with other countries we had to collect the data for the manufacturing industries in the Federal Republic Germany. There existed a few time series in the form of a "Saarbruecken File¹ " from 1961 to 1975 incorporating 400 firms. For a significant portion of missing values for the respective years we collected those numbers from "Hoppenstedt Handbooks ". From the "Saarbruecken File " we selected 299 firms for the following reasons :

- We found complete data for our required calculations for the time period 1961 through 1982.

- we did not select stock companies (AG's) which were not in manufacturing industries.

- We also excluded the stock companies whose legal form (Gesellschaftsform) has changed during this time period and those which disappeared through mergers activities.

- We did not consult companies with other legal forms.

6.1.1 Overview of sources

For the sources of data for Germany we consulted the following publications:

- Hoppenstedt: Handbook of Stock Companies (AG's)

- Financial reports of the firms

- Statistical yearbooks

¹This file contained all variables from which we could calculate the desired profit rate. The data was collected by Prof. Poensgen and his colleagues.

6.1.2 Selection of the time period 1961–1982 for FRG

We started our time period with 1961 because in 1959 major revision of publication requirements were put into effect in the German corporate laws¹. For example, until 1959 rather than reporting gross sales companies reported the sales net of purchase of raw materials. According to the old corporation law of August 15, 1969 the German Corporation laws required annual publication of financial reports. Stock Companies and Scrip Companies were required to publish their annual reports regardless of their size on the other hand the Limited Liability Companies had to disclose their informations according to their size.

Since the begining of 1986, only companies of the type Stock Companies (AG's), Scrip Companies (KGaA) and companies with limited liability (Gmbh's) are required to publish their financial and business activities report, if a minimum of two out of the following three size characteristics apply:

- Total assets exceed 15.5 Million DM.

- Total sales exceed 32 Million DM.

- Number of employees exceeds 250 workers.

According to these new requirements there would be more company reports available. For our sample time period, 1961–82, we can see from figure 6.1 that the number of companies decreased over time. On the other hand, the number of companies with limited liability increased from 16395 to 60893 for this time period (not reported in the figure).

¹ see Woehe (1984), p.303–4, Schubert and Kueting (1981) and Schwalbach and Mahmood (1990), p.107–108.



6.1.3 Descriptive statistics

In this section we report the results of descriptive statistics. The after tax definition of profit rates is used for both countries and are not normalized¹.

Table 6.1 reports the summary statistics of both the countries. Each mean, standard deviation and the coefficient of variation were calculated for each year using the crosssection of sample firms and then averaged over the observation period.

The mean profit rates across firms and over time between two countries for 1961–82 and 1950–80 are 4.83, 7.200. The mean profit rate is lower in Germany than the US.

These results are similar with those of the US sample of 600 firms for the 1950–72 series and 438 firms for the 1964–80 series. For both the series a high mean value was found.

The mean standard deviation is almost equivalent in both countries, suggesting that the dispersion of profit rates across firms in Germany is lower than in the US. These results are consistent with those of reported in Odagiri and Yamawaki(1990), who also found that the standard deviations are equivalent for both countries.

Comparing the mean values of the coefficient of variation (CV) between two countries, we find a higher value for Germany than for the US. These findings are again not consistent with the results of Odagiri and Yamawaki(1990). From these results we conclude that the dispersion of profit rates across firms is lower in Germany than in the US.

¹ Profit rates are defined as after tax plus interest divided by total assets and are not normalized.

Table : 6.1

Means and standard deviations of time series of unnormalized profitrates:

		30
	FRG	USA
Mean	4.833	7.200
Standard		
deviation	3.998	3.864
Coefficient		
of variation	.868	.348
N of firms	299	500

6.1.4 Normalization method and profit definitions.

The empirical studies of Mueller (1983), Odagiri and Yamawaki (1985) first used the normalization method of " by ratio " (see also p.7), i.e.,

$$\Pi_{it} = (P_{it} - \overline{P}_t) / \overline{P}_t$$

but the latter found for Japan that the mean profit rate and the variance across companies were negatively correlated over time, implying that the inter-company profit rate variance moves counter-cyclically to the mean rate. So this normalization method resulted in an over (under) estimation of the extent of inter-company profitability differences in a year with low (high) average profitability. They further used the normalization method of " by deviation " i.e. $\Pi_{it} = \Pr_{it} - \overline{\Pr}_{t}$, where \Pr_{it} denotes the profit rate of firm i in the year t, and $\overline{\Pr}_{t} = \sum_{i=1}^{n} \Pr_{it} / n$, the across company average in year t and n is the number of companies. Our study (Schwalbach and Mahmood (1987)) used the " by deviation " method and four different profit measures: Therefore, the subsequent analysis will only apply the " by deviation " method and before tax and after tax measures which are defined as :

1) Nominal profit rate on total capital before tax, defined as profit available for dividend plus interest payments plus income tax payments divided by total assets.

2) Nominal profit rate on total capital after tax defined as (1) but after tax.

¹ Recent criticism was made on the use of accounting profit measures (see Long and Ravenscraft(1984), Smirlock et.el. (1984) and Mueller(1990), Appendix)).
6.1.5 Result of trend and business cycle for FRG

Figures 6.2 and 6.3 displays the movement of the mean rate of return¹ and their standard deviations for the definitions after tax (AT) and before tax (BT) over the time period 1961 through 1982. Both of the definitions indicate a clear downward trend² but it is more severe for the BT. The standard deviation curves indicate for AT and BT that the profitability fluctuation around the mean across firms is not high for the years 1961–73 but it is higher between the years 1973–82, which suggests that the profitability difference is severe for the latter time period.

Table 6.2 summarizes the regression results of the six equations in which we regressed the mean rate of return (MRR) before and after tax against time and the business cycle indicator variable, rate of capacity utilization (RCU = measured as the share of plants utilized with full capacity)³ for both of the definitions in order to analyze the effect of trend and business cycle. Equation (1) exhibits the expected negative significant coefficient of the time variable which clearly suggests a decline of MRR over time. In the second equation we added the business cycle variable which is positive but statistically insignificant. This implies that the business cycle does not have a severe effect for the respective time period but the time coefficient still remains significant with a negative sign.

¹ MRR_t = $\sum_{1}^{N} PR_t / N$, where t = 1,22 and N=299 the number of firms. Furthermore the

outliers (values greater than 2 X standard deviations) were removed for specific years from the data.

 $^{^2}$ The results are consistent with Funke (1987), see also Albach(1985), Neumann et.el.(1983) and Schwalbach(1985).

³ RCU =(Source: Main economic indicators, various years,OECD).



.





Table : 6.2

Regression analysis : Mean rate of return for manufacturing corporations 1961-1982

	Explanatory varia			
Equations	Time	RCU	TRCU	R^2
After tax				
(1) MPR	10315 (9.692)			.8157
(2) MPR	0948 (6.787)	.01991 (.927)		.8144
(3) MPR	.0803 (.2774)	.0468 (.9457)	00208 (6055)	.808
Before Tax				
(4) MPR	3095 (-16.061)			.924
(5) MPR	2962 (-11.653)	.03198 (.8186)		.923
(6) MPR	.9063 (2.013)	.2157 (2.815)	0438 (-2.674)	.942

Note : t-statistics in parenthesis and all equations were estimated using ordinary least square.

Now, if we add another variable TRCU^1 the coefficient of time becomes positive but statistically insignificant, whereas the RCU coefficient remains almost the same as in equation 2. The negative insignificant coefficient of TRCU suggests that the business cycle has a decreasing effect over this time period. The results of equation 4 and 5 are similar to the first and second equation but a substantial difference is observed for equation 6. The coefficient of time is statistically significant and positive whereas the coefficient of TRCU is negative but significant, which suggests a highly decreasing effect of the cyclical fluctuation over time². This implies that the coefficient becomes significant because of the difference in tax systems. All equations exhibit a large value of R² (adjusted for degree of freedom). For the three equations using AT definitions it can be concluded that more than 80% of the variance of the mean rate of return can be accounted for by the explanatory variables and for the BT definition the value of R² even increases to more than 90%. These results suggests that all equations posseses a very high explanatory power.

Note: We calculated the average period according to the formula

 $\cos \frac{2 \Pi}{p} = \frac{\phi_1}{2\sqrt{-\phi_2}}$ taken from (see McLeod (1982), p. 11–81, and also Jenkins

(1979, p.98)) and did not find cyclic behavior of the time series.

¹ TRCU = RCU * Time(Time multiplied to observe the effect of later periods).

 $^{^{2}}$ Rate of return was regressed on other explanatory variables (see Albach (1984), Schwalbach and Mahmood(1990)).

6.1.6 Projected and predicted profits of few firms for FRG

Figures 6.4 – 6.8 provide some initial insights into the process of convergence (For US sample see Mueller (1986)). We will illustrate how different models capture this pattern. In order to plot these figures against time we defined the dependent variable in terms of profit deviations¹ in each of the estimated profit projections. The dotted line is the raw profit rate ² (RAW), the dashed line the predicted profit rates (BF) selected as the best fit of the three polynomial in 1/t(B) and the predicted profit rate of the lag model(LAG). For the order we selected few companies from the entire sample with different patterns.

Examining figures 6.4 and 6.5 it can be seen that Daimler-AG and Hoechst-AG start with a profit level which is above the competitive (For definition see Geroski(1990)) mean in the initial years and then rises slightly before starting to decline continuously from the year 1965 while still remaining after 22 years above the competitive mean.

Stumpf-AG's profit (Fig: 6.6) is slightly above the mean and does not move away from the mean and converges to the competitive mean until 22 years.

A different pattern is illustrated by the company Dynamit–Nobel–AG (Fig: 6.7) whose profit level is below the mean and starts continuously rising and approaches the competitive mean after 22 years.

Finally, Paul-Hartman-AG (Fig: 6.8) exhibits a profit at the initial periods around the mean, which after a few years starts rising continuously and remains after 22 years above the mean. Out of 299 companies a substantial number exhibits a behavior like Paul-Hartman-AG, we also identified a significant number of companies with patterns resembling those described in the other figures.

¹
$$\Pi = (\Pi_{it} - \Pi_{it})$$
, where $\overline{\Pi}_{it} = \sum_{i=1}^{N} \Pi_{it} / N$ t=1,22 and N = Number of firms

² The spikes noted in all figures for some years are outliers which we detected when the models were estimated.











7. Regression results of deterministic models

7.1 Results of polynomial models

The sample used in this time series consists of 299 German manufacturing firms for which data were provided from 1961 through 1982. We estimated¹ for each firm in the sample the parameters $\hat{\alpha}$ (ST), $\hat{\alpha}$ (BF) and finally provided the estimates of partial adjustment model $\hat{\alpha}$ (PA) from the sections 1.1 and 1.2.

Table 7.1 provides the results of simple correlations between different long run profit projections $\hat{\alpha}(ST)$, $\hat{\alpha}(BF)$ and $\hat{\alpha}(PA)$, mean profit rates (II) over a 22 year sample period, and the initial profit rates: INPR = ($\Pi_{61+62/2}$). The profit projections $\hat{\alpha}$ (ST) and $\hat{\alpha}$ (PA) are positively correlated with initial profits and mean profits but negatively correlated with $\hat{\alpha}$ (BF), which implies that a company initially earning a higher-than-average profit rate tends to maintain its profit rate even in the long run for $\hat{\alpha}$ (ST) and $\hat{\alpha}$ (PA) but the opposite with the $\hat{\alpha}$ (BF) model. The highest correlation coefficients are found between $\hat{\alpha}$ (ST), $\hat{\alpha}$ (PA) and $\overline{\Pi}$ which range between .8107 and .9350. Mueller(1986), Odagiri and Yamawaki(1986) also found a fairly high correlation between all profit projections, but the poorest one was for " best fit " polynomial in 1/t. Our earlier results (Preliminary results are not reported) which were based on a sample of 191 companies and time period 1961–1981 also suggested similar behavior to our present correlation results only with a slight difference, we found that the best fit correlation coefficient shifted from +ve(.0634) to -ve(-.1911).

¹ The following regression programs were used : TSP 4.0 WZB-version, SHAZAM 4.4 installed at CD- Cyber of Free University and RATS 4.3, SHAZAM 6.1 IBM-PC-AT. Wordprocessing and Graphic were done with T^3 and CHART on IBM-PC-AT.

Table : 7.1

Simple correlation coefficients matrix

	1	2	3	4	5
	ά(ST)	ά (BF)	ά (PA)	Π	INPR
1	1	.3793	.8325	.9350	.4500
2		1	.4432	.2410	191
3			1	.8107	.3283
4				1	.6920
5					1

N = 299

We additionally regressed the projected profits on initial profits for both linear and quadratic specification.

Table 7.2 presents the regression results of the estimated equations. A significant relationship between projected profitability and initial profit rates could not be found for every equation. The coefficient of the initial profit rate in all equations has a positive sign and is statistically significant except for the BF equations. Only for the PA2 projection is the linear specification the best, which implies that for every one percent that a firms profits were above(below) the average profit rate of all firms in 1961–62, they are projected to be .2 percent above(below) the average into the indefinite future.

The negative coefficients of the squared initial profit rate implies that after a point, the further is a firms profits are from the mean, the greater is the percentage movement toward the mean. The equation PA2 implies that a firm earning double the average profit rate in 1961–62 will earn, on the average 35 percent more into the indefinite future. From the PY1 and PY2 (Π) equations it can be seen that a similar positive relationship exists between PY1, PY2 and initial profits.

Table : 7.2

Dependent variables	Intercept	INPR ₆₁₊₆₂	INPR ² ₆₁₊₆₂	R ²
ST	000182 (0917)	.2371) (8.71)	,	.202
ST	00102 (464)	.222 (6.9)	.1559 (.902)	.2009
BF	00171 (512)	15020 (-3.28)		.0320
BF	00062 (.1700)	1084 (-2.0)	4355 (-1.6)	.0361
PA1	.00047 (.065)	.1722 (4.3)		.0564
PA2	.00341 (2.16)	.1701 (5.9)		.1052
PA2	.00517 (2.28)	.2536 (7.9)	3696 (5.02)	.1728
PY1	.00002	.31330 (11.6)		.312
PY1	.00038 (.434)	.32020 (11.4)	4566 (82)	.3113
PY2	.00006	.36560 (16.6)		.4780
PY2	.000385 (.2154)	.37137 (14.4)	05941 (422)	.4766

OLS-Regression results of profit projection on initial profit rate N = 299

: t-statistics are in the parenthesis.

The results for the goodness of fit for the models show that the R^2 (adjusted for the degrees of freedom) for our sample was found more often positive then the negative. The modest criteria of .1 was achieved in 236 cases or 78.9% of the 299 companies. In our earlier sample of 191 firms we had 48.6%, so with the larger sample the goodness of fit has substantially improved. For the best fit model we selected the highest R^2 which has considerably increased to 262 cases or 87.6%, if we compare this to our earlier results of short sample which was 67.3% we can observe an improvement.

In considering the extent of the persistence of intercompany profit rate difference among convergence models we can clearly conclude that the best fit model had poorer persistence of profit that did the standard models. The ordering of subsamples for the best fit model was quite ambiguous (The results are not reported in the table 7.3). From column 1 of the table 7.3 it can be seen that the ordering of subsamples for the standard model is consistent with that of the initial profit rate. The first column shows that the first subsample has the highest estimate, followed by the second, third or fourth and finally by the two subsamples at the bottom.

The columns second and third in table 7.3 show the number of positive $\hat{\alpha}$'s which are greater than zero and the percentage of the number of companies within the group.

In the first group $\hat{\alpha}$ was found to be positive of the 50 companies, which accounts for 66 percent of the first subsample. In the whole group there were 128 companies with positive $\hat{\alpha}$'s which accounts for 42 percent.

The distribution of the mean of $\hat{\beta}$, which is the measure of the speed of convergence to the normal rate is consistent with the initial profit rate. The absolute value of the mean $\hat{\beta}$ is small in this sample, which implies that the speed of convergence¹ is smaller for Germany.

¹ Schohl (1989) did a analysis of variance test and found a convergence process more stronger than our results (see also Levy (1987)).

Mean $\hat{\alpha}$'s and $\hat{\beta}$'s by subsample of standard model

Sample 299 Firms Time Period 1961–1982 Before Tax

N of Firms	Mean Λ α	Number of $\hat{\alpha} > 0$	Percentage $\hat{\alpha} > 0$	Mean β	INPR
50	2.923	33	66	.0839	12.162
50	0.419	24	48	.0443	4.364
50	0.359	26	52	.0043	0.358
50	-0.353	21	42	-0.0267	2.906
50	0.886	16	32	0.0391	-5.104
49	2.571	8	16	-0.0692	-8.631

The positive $\hat{\beta}$ imply falling profit profit rates and negative the rising profit rates. In terms of β percentage for the whole sample we found 134 companies which makes 44 % and is quite similar to the $\hat{\alpha}$ distribution.

7.1.1 Comparison of FRG and US results

To examine whether the profit persistence based on these models differs across two countries we compare our standard model results with Mueller's (1983) for the US. He used a sample of 600 companies in 1950–72 and the after tax definition, whereas we used the before tax definition.

The distribution of $\hat{\alpha}$ across the subsamples is not similar because in our third group Germany has a positive mean compared to the negative mean of the 3rd US subsample, the percentage of $\hat{\alpha}$ is greatest for the US for the first, second and the last subsample and for Germany in the third, fourth and fifth group.

The distribution of the mean of $\hat{\beta}$ clearly differs. The absolute mean $\hat{\beta}$ are larger in the US, which imply that the weaker significance of $\hat{\beta}$ suggest that the companies profit rate equalization tendency exits.

7.2 Results of PA-model for FRG

Tables 7.4 and 7.5 summarize the estimated results¹ of the partial adjustment model described in section 1.2 for both the after tax and before tax definitions.² The results are based on the normalization by the deviation method. Tables 7.4 and 7.5 present the results in which we detected the outliers³ (see Andrews, et.el.(1978) test for examining outliers, Rousseeuw, et.el. (1987) and Tsay (1986)).

Following Mueller's (1983) methodology we calculated the initial profit rate (INPR) as the average over the begining two years (1961–62) and then grouped the companies in the order of the INPR into six subsamples first five of 50 companies and last of 49. The average of the estimated long-run projected profit rate $\hat{\alpha} = \hat{\alpha} / 1 - \hat{\lambda}$, the estimated slowness of the convergence $\hat{\lambda}$ and $(1 - \hat{\lambda})$ as the estimated speed of convergence. We did not find any $-1 < \hat{\lambda} > 1$ (because profit rate explodes in the long run). From table 7.4 it can be seen that the ordering of the PPR across the six subsamples for both of the definitions is the same as for the initial profit rate

¹ Our present results were corrected for small sample bias by multiplying the estimated coefficients by T/T - 2 from the model $Y_t = \hat{\beta} Y_{t-1} + \varepsilon_t$, where $|\hat{\beta}| < 1$ and ε_t is a zero mean, the small sample bias is approximately equal to $-2\hat{\beta}/T$, where T is the number of observations in the sample (see Johnston(1972), p.305-6, Geroski and Jacquemin(1987)). ² In our previous results we estimated four different profit measure (see Schwalbach and Mahmood(1987)).

 $^{^{3}}$ The values greater than the 2 x standard deviations were dropped from the sample. In addition we also estimated the models including dummy variable, we do not report the results because not a significant results were achieved for both definitions.

Outlier detected model

Def: Before tax

Subsamples	â	â	INPR	N of Firms
1	2.515	0.376	12.039	50
2	0.746	0.536	4.292	50
3	0.809	0.665	0.278	50
4	-0.320	0.558	-2.955	50
5	-0.547	0.478	5.144	50
6	-1.307	0.479	-8.685	49
1	5.629	0.522	9.690	21
2	1.500	0.684	1.654	21
3	0.665	0.690	-1.119	21
4	-1.153	0.666	-3.569	21
5	-1.353	0.576	-5.793	21
6	-1.476	0.545	8.594	20

Note :All equations were estimated using OLS- method, Mueller (1989), Odagiri and Yamawaki (1989) also used Cochrun- Orcutt method to detect autocorrelation.

Outlier detected model

Def : After tax

Subsamples	â	â	INPR	N of Firms
1	0.532	0.483	4.534	50
2	0.363	0.730	1.618	50
3	0.537	0.666	0.163	50
4	0.238	0.564	-0.871	50
5	0.413	0.609	-1.178	50
6	-1.125	0.594	-1.374	49
1	2.159	0.663	3.138	17
2	1.544	0.670	1.119	17
3	0.390	0.754	-0.019	17
4	0.021	0.690	0.932	17
5	-1.348	0.797	-1.940	17
6	2.225	0.695	-3.43	18

but different in the third subgroup which has a slightly higher value than the second subsample for both the definitions.

The 50 companies in the first subsample which have the highest estimates earned on average between 4.5 to 12.0 percentage points higher profit rate in 1961–62 than did the average of all the companies in this sample, and still earned .5 to 2.5 percent higher profit rate even in the indefinite future. Now in contrast in the last subgroup the 49 companies earned between -1.3 to -8.6 percent lower profit rate in 1961–62 than the average of all the companies in this sample , are estimated to earn -1.1 to -1.3 percent lower rate below the average.

It can be concluded that the firms earning a higher-then-average profit rate are at one point in time on average expected to earn a higher-then-average profit rate even in the long run for both the definitions.

The second column presents the means of $(1 - \hat{\lambda})$ for each subsample. We do not observe a systematic pattern from subsample to subsample . The subgroup with the highest estimates exhibits the lowest $(1 - \hat{\lambda})$ of .376 and .483 for both of the definitions. This implies that the companies in these subgroups where profit remained above the mean in the long run have the slowest speed of convergence. This may also suggest that the highly profitable firms were able to protect their market positions fairly well.

The results which were obtained from the tests we applied to the models are now considered in terms of the significance of $\hat{\alpha}$ (which we calculated according to the formula described in section 1.3) we found 58 cases significantly positive, this accounts for 19.4 percent and 50 (16.7) for the after tax definition and significantly negative 53 (17.7%) for before tax and 84 (28.1%) for after tax.

The number of cases for which $\hat{\lambda}$ is significantly positive (ten percent level, one tailed test) is 204 (68.2%) for before tax and 240 (80.3%) for after tax. No $\hat{\lambda}$ were found to be significantly negative (ten percent level two-tailed test) out of our entire sample.

The number of cases for which R^2 (adjusted for degrees of freedom) is greater than zero was 190, which accounts for 63.5 percent for before tax and 232 cases (77.6%) for after tax. We further calculated the correlation coefficients between projected profit rates, average profit rates and initial profits. The correlation coefficient between PPR and INPR ranged from .2437 to .3448 and between PPR and the average profit rate from .736 to .811 for both the after tax and before tax definitions. The high positive correlation between these estimates suggests once again the existence of abnormal profits even in the long run. In comparison to the US correlations these estimates are relatively small.

The lower half of table 7.4 presents the results which include only the significant equations¹ (two tailed, test five percent level of significance) in terms of $\hat{\lambda}$ and where companies are grouped in six subsamples according to the initial profit rates. The number of companies in both the definitions were substantially reduced to 125 and 103 respectively. Furthermore, a stronger evidence of persistence in terms of $\hat{\alpha}$ is obvious, particularly in the first subsample. The 17 companies in this group earned 3.1 percent of their average profit during 1961–62 above the average and after 22 years they still earned a profit rate that was 2.2 above the mean. A similar behavior can be seen for the first group for the before tax definition. A very consistent pattern of the ordering of $\hat{\alpha}$ is observed for both the definitions as is shown by coulmns 1 and 5 in the lower half of table 7.4. The distribution of $(1 - \hat{\lambda})$ is quite similar to the results in the upper half of the table, but the magnitude of the value has increased across all subgroups. The first subgroup for both of the definitions still has the lowest value. This implies that in this subgroup the speed of adjustment is relatively high.

¹ A further exercise was considered the significant equations in terms of $\hat{\alpha}$'s but the grouping of the estimates was found to be ambiguous. Thus, we do not report the results here.

7.3 Results of PA-model for the US

Tables 7.6 and 7.7 reports the results of 500 US companies for the time period 1950–1980¹. We report the results with both outliers detected and dummy variable included model. Columns one and five show that the ordering of $\hat{\alpha}$ across subsamples is consistent in the sense that the first subgroup has a larger persistence than the second , third and so on, including the initial profits. The second and sixth columns show the distribution of $(1 - \hat{\lambda})$ across the subgroups, which has a mean around .6 for both the models. The lower part of the table, which reports the results of only the significant equations, in terms of $\hat{\lambda}$'s, shows that the extent of persistence changes across groups for both the models. For the first group 39 companies earned their profit 6.9 percent above the norm at the average of 50+51+52/3 and after 31 years they still earned 4.5 percent above the mean of 2.9 found for the upper half of first group. The values of subgroups two and three have also increased. The distribution of $(1 - \hat{\lambda})$ across subsamples has not greatly changed.

Now, we consider the results of tests made for the significance of different estimates. The number of cases for which $R^2 > .1$ increased from 117 (21.2%) of Mueller's sample results of 551 companies for the time period 1950–1972 to 332 (66.4%) for the outlier detected model and we additionally found for the dummy model 353(70.6%) cases for which R^2 was greater than .1. These values show that the fit of the model has substantially improved. The number of significant positive cases of $\hat{\alpha}$ (calculated with the formula described in section 1.3) increased from 125 (22.7%) of Mueller's to 161 (32.2%) and 163 (32.6%) for both models, or the negative significance the number of cases decreased from 149 (27%) to 80 (16.0%) and 85 (17.0%).

The number of cases with a positive and significant $\hat{\alpha}$ substantially increased from 152 (27.6%) to 384 (76.8%) and 378 (75.6), respectively. Furthermore, no $\hat{\lambda}$ which exceeded the value greater than one was found to exist.

Table : 7.6

Outlier detected model

Subsample	â	â	INPR	N of firms	
1	2.975	0.565	6.266	84	
2	1.566	0.636	2.289	84	
3	0.927	0.636	0.450	83	
4	0.188	0.639	-1.082	83	
5	0.243	0.605	-2.531	83	
6	0.736	0.576	-5.228	83	
1	4.649	0.554	6.912	39	
2	3.124	0.717	3.175	39	
3	2.775	0.707	1.189	38	
4	1.059	0.653	-0.457	38	
5	0.446	0.678	-1.217	38	
6	0.894	0.627	-1.503	38	

Note: Source of US data: Moody's manuals for US (The data were collected for the years 1973-1980, and the data for 1950-72 were used by the permisson of Prof. Mueller.

Table : 7.7

Dummy model

Def: After tax

				-
Subsamples	â	â	INPR	N of Firms
1	2.960	0.571	6.266	84
2	1.560	0.644	2.289	84
3	0.913	0.654	0.450	83
4	0.173	0.649	-1.082	83
5	0.249	0.620	-2.531	83
6	0.748	0.614	-5.228	83
1	4.625	0.560	6.912	39
2	3.004	0.717	3.189	39
3	2.782	0.717	1.122	39
4	0.988	0.653	0.475	39
5	0.365	0.697	-1.218	38
6	-0.966	0.663	-1.516	38

Note : Again a model as $Z_t = \alpha + \beta Z_{t-1} + \delta Dummy_t + \varepsilon_t$ was estimated for each equation, where the outlier was assigned a value of 1 and otherwise 0. (see Younger (1979), section 15.3)

7.4 Results of LM-test

We estimated the regression for each firm i in order to perform two different specification $tests^{1}$ as described in section 2.

First, with the residuals from equation 14 the three equations including residuals as dependent variables were regressed against the lagged profit rate variable and lagged residuals upto the 3rd order, than the R^2 was multiplied by the sample and the values for the Chi-square were calculated and then compared to the critical values in the table.

Secondly, the residuals were included in addition to the lagged variables as independent variables, the three equations were estimated using the profit rate as the dependent variable. The appropriate F-statistics (see Kmenta(1971), p.371) were calculated with 18,17,16 degree of freedom respectively. The tabulated critical values at 5% significance level are $F_{2,18}$ = 3.55, $F_{2,17}$ = 3.59, $F_{2,16}$ = 3.63 and at 1% level of significance 6.01, 6.11, 6.22.

For the first test the $\hat{\rho}$'s was not significantly different from zero at 5% level of significance for 23 firms.

For the second test the $\hat{\rho}$'s were not significantly different from zero at 5% and 1% level for 39 equations. The distribution of the rejection of the order of $\hat{\rho}$'s was for 5% level rather different for respective degree of freedom. We excluded a additional 39 firms (misspecified models) from the sample and grouped them into six subsamples as already illustrated in the previous sections.

¹ see also Schwalbach and Mahmood (1990).

		· · ·			
Subsamples	â	ŝ	INPR	N of Firms	
1	.329	.492	4.577	46	
2	.392	.711	1.674	46	
3	.481	.649	.158	46	
4	.238	.588	910	45	
5	341	.602	-1.798	45	
6	-1.141	.592	-3.767	45	

From table 7.8 we conclude that after dropping the misspecified models from the sample the value of $\hat{\alpha}$ is quite similar to those of in table A column five. The distribution of $(1 - \hat{\lambda})$ still remains consistent across the subsamples and the magnitude of the values of $(1 - \hat{\lambda})$ remains virtually the same.

7.5 Summary

In this section we estimated the polynomial and partial adjustment models for 1961–82 series of Germany and 1950–80 series of the US. According to both definitions of Germany a downward trend is observed and it is further found that the business cycle does not have any significant effect.

The regression results of polynomial models show for Germany that a company initially earning a higher than average profit rate tends to maintain its profits even in the long run for standard model and partial adjustment model but the opposite is found for the best fit model. If we consider only the statistically significant equations, the magnitude of mean profit rate increases but the effect is substantial for the US. The mean value of the speed of adjustment remains stable across subgroups and of the subgroups of insignificant equations. The results of significance tests show that the fit is substantially improved but particularly for the US sample. Finally, the results of LM test showed that for 13 % the models were misspecified but they did not influence the systematic of persistence of profits.

8. Regression results of stochastic models for FRG

8.1 Results of first-order autoregressive model

In the previous chapter we reported the results obtained from the polynomial and PA- models. In this chapter we will report the results obtained from the stochastic models. We first explain the results of the first order autoregressive model described in section 3.6.1.

In order to keep our results comparable with the PA- model (see section 1.2) we will transform our estimated parameters $\hat{\varphi}$ and $\hat{\delta}$ such that $\hat{\lambda} = (1 - \hat{\varphi}_1)$, $\hat{\alpha} = \hat{\delta} / (1 - \hat{\varphi}_1)$ and refer to them again as the speed of adjustment and projected profit rate, respectively, throughout the next sections. We estimated the model mentioned above for each equation of the 299 companies using annual data for the time period 1961–1982. In order to check the stationarity¹ condition we calculate the roots of all 299 equations. We found for two of the firms the roots less then unity in absolute values, which implies for these two firms the process exhibits non stationarity. Thus, we excluded these two firms from the sample. We repeated the process of building up the subsample as described in the previous sections. Table 8.1 reports the results in the upper half in which all significant and non-significant parameters were retained and in the lower half in which we retained only those equations which were statistically significant in terms of the φ parameter. Columns one and four of the table show that once again the ordering of $\hat{\alpha}$ accross subsamples is quite consistent with those of the INPR (initial profit rate).

¹ The bounds of stationarity for an AR(1) process are determined by the roots of the characteristic equation $(1 + \phi_1 B) = 0$, i.e., if the process is stationary, then the roots must be greater than unity in absolute value, implies $|\phi_1| < 1$, for equation (see McCleray and Hay (1980)).

Table : 8.1

Subsamples		â	î	R^2	INPR	N of firms
	1	1.787	.423	.465	4.396	50
	2	0.379	.702	.363	1.558	50
	3	0.392	.620	.314	0.116	50
	4	0.210	.524	.424	0.900	49
	5	-0.915	.596	.402	-1.793	49
	6	2.148	.557	.488	-3.735	49
	1	2,334	.351	.513	4.937	31
	2	0.235	.421	.502	2.108	31
	3	0.505	.455	.432	0.131	31
	4	0.495	.407	.463	-0.926	31
	5	-0.760	.428	.482	-1.727	30
	6	-2.245	.378	.555	-3.666	30

The value of the first subsample has changed substantially from .532 of the PA-model to 1.800 of this autoregressive model which implies that the companies in the highest group are the most persistent with this model. The values of $\hat{\alpha}$ of other subgroups resembles with those of the PA-model. From column two of the table the distribution of the mean $\hat{\lambda}$'s across subgroup is also consistent with those of the PA-model. The first group still has the smallest mean .423 as in the first group of the PA-model.

Now, we look at the lower half of table 8.1 in which only those equations were retained which are statistically different from zero at the 10% level of significance. For the remaining 184 companies or 62% the value of the first subgroup has again changed from 1.70 to 2.33 and the value of the second subgroup has decreased but has increased in subgroups three and four. As column two indicates the mean value of $\hat{\lambda}$ has decreased across subgroups and its value is about .4. If we consider only significant estimates the predictive power of the results improves. Column three in the upper and lower halves of the table presents the means in term of \mathbb{R}^2 (adjusted for the degree of freedom) but its usefulness is restricted because of the nature of the estimation process. Still its value is about .45, implying that 45% of the variance in the time series is explained by the model for each group.

From the following equation, which presents the average means of all 297 equation, we can see the overall significance of the estimates of the sample :

$$(1 - 0.429B) Z_t = -0.00059 B = 2.33$$

(2.48) (-0.0745)

The numbers within the parentheses are t-ratio's and the number 2.33 on the right side is the size of the root. The estimates of this equation suggests that stationarity has been achieved for 99% and the significance of the parameters ϕ has been achieved for a relatively large number of equations in the sample.

8.1.1 Specification test of AR(1)

The portmanteau test (described in section 5.1.1) on the residuals will be applied to all equations to check the adequacy of the model. If the fitted models are appropriate, (i.e., if the errors are white noise), this statistic is approximately as a \aleph^2 distributed variable. The 10% and 5% points for \aleph^2 with 10 degrees of freedom are 16.0 and 18.3, respectively. Since the statistic is a measure of correlation among the residuals, its value should be as small as possible indicating that the models are correctly specified. On the basis of this test we found at the 10% level of significance 17 companies for which the calculated value exceeded the tabulated value. Further, at the 5% level we found that the model was rejected for eight companies. We eliminated the 17 and 8 equations, respectively, from the sample and reconstructed the subgroups as in table 8.1. The results are not reported because the values of $\hat{\alpha}$ and $\hat{\lambda}$ were negligibaly changed across subgroups and the ordering of the both estimates remained consistent as reported in table 8.1.

8.2 Result of second-order autoregressive model

In order to evaluate the question, whether each firm follow a lag period of longer than one year, we extend our model from the last section to another lag variable,

$$Z_t = \delta + \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \varepsilon_t$$
 or in the backshift form

$$(1 - \phi_1 B - \phi_2 B^2) Z_t = \delta + \varepsilon_t$$
, where ϕ_1 and ϕ_2

are the parameter to be estimated. We will define $\hat{\lambda} = (1 - (\hat{\varphi}_1 + \hat{\varphi}_2))$ and

 $\hat{\alpha} = \hat{\delta} / 1 - (\hat{\phi}_1 + \hat{\phi}_2)$. The parameters ϕ_1 and ϕ_2 were estimated separately again for each equation. In checking the stationarity¹ of the model, i.e. we calculated the roots² of the characteristic equation for all firms i in the sample, there were 46 equations for which the roots were less than unity. This led us to suspect that the parameters were unstable, so we excluded these equations from the sample. We were left with a sample of 253 or 84.6% firms from which we constructed the subgroups in table 8.2.

Looking at column one we can see that the estimates of the means for first, second and third subgroups are increased in magnitude in comparison with the respective subgroups of the AR(1) model.

¹ The bounds of stationarity for an AR(2) process are $\phi_1 + \phi_2 < 1$, $\phi_2 - \phi_1 < 1$ and $|\phi_2| < 1$. ² Root = $\sqrt{(\text{Real})^2 + (\text{Imag})^2}$ for B₁, B₂ > 1. The third subsample of column four shows that the value has become negative and is

- 0.126% below the competitive mean, and its relevant PPR value is positive at 0.649%. Comparing the relevant estimates of the AR(1) model, we observe an improvement for this subgroup. From column two we observe an increase in the mean values of $\hat{\lambda}$ across subgroups suggesting a higher speed of adjustment in comparison with the $\hat{\lambda}$'s of AR(1) model. The R² values from column three are again around .4 across subgroups suggesting a relatively good fit of the estimates.

To check the significance of the equations in terms of the ϕ 's parameters the first lag parameter $\hat{\phi}$ we found for a substantial number of equations 141 or 55.9% the coefficient statistically different from zero. We further estimated a correlation of -.07494 between $\hat{\phi}_1$ and $\hat{\phi}_2$ for these 141 equations which suggests that there is less dependence between these parameters, implying that the model does't need any simplification. We further found 30 companies or 12% for which the first and second lag coefficient were statistically significant and their correlation coefficient - .3359 which suggest that for this group of companies a second order lag model is appropriate. Furthermore, we found for 87 or 34.5% of the equations for which both coefficient were statistically insignificant and their correlation coefficient .347, this suggests that for these equations the estimated model may need simplification. Finally, a correlation coefficient .0907 for all 253 stationary equations suggests that the overall fit with this second order model can be justified. Examining the 30 companies with both statistically significant parameters reveals that these companies are allocated to 12 different industries. This implies that for a firm with higher significant lag it is not important to be in a profitable or non-profitable industry and suggests that the length of adjustment period does not posses any systematic tendencies.

Table : 8.2

1.1

Subsamples		â	î	R ²	INPR	N of firms
	1	1.842	.525	.442	4.143	42
	2	0.539	.813	.359	1.234	42
	3	0.649	.715	.338	-0.126	. 42
	4	-0.216	.587	.404	-1.091	42
	5	-1.463	.639	.457	-1.903	42
	6	-2.767	.585	.483	-3.926	43
The projected profit rate (PPR) and initial profit rate (INPR) of five companies from the pharmaceutical-chemical industry which is the most profitable industry is examined for the company Beiersdorf AG INPR is 3.7% and PPR is 9.45%; for Riedel-de Haen AG's the INPR is -.738% and PPR is .666%; for Paul Hartmans AG's .78 and 7.48 percent; for Reichelt AG's 4.31 and 1.45 percent; and finally for Wolfs-Walsdorf AG's the INPR 1.18 and -.262. So the results estimates suggests that even these firms need for their profit adjustment longer than one period, so according to their initial profit average of (61 + 62)/2 they still tend to earn below (above) the competitive mean, even in the long run.

The overall significance and stationarity for all 253 companies is identified by

$$(1 - .384 \text{ B} + .028 \text{ B}^2) Z_t = -.00102$$
 $B_1 = 10.257 B_2 = 3.482$
 $(1.63) (-.137) (-.0934)$

The numbers within the parentheses are again the t-ratios. The values of both roots B_1 and B_2 indicates that they lie outside the unit circle, this implies that the overall stationarity is well represented by this autoregressive model of second order. The t-ratio of the first lag also suggest for a substantial number of the equations the statistical significance, whereas from the t-ratio of the second lag we can feel insignificance for a broader number of the equations, since for a majority of the equations the second order parameter has been found insignificant. However, a low correlation coefficient .09 indicates that there is no need to drop the second parameter from the respective equations.

8.3 Results of third order autoregressive model

Table 8.3 reports the results of the autoregressive model of third order¹. After having calculated the roots of each equation of the whole sample, there are 95 equations for which the roots were less than unity, i.e these parameters exhibited non-stationarity. These equations were therefore dropped from the sample. The results are finally, reported only for sample of 205 stationary equations. We define $\hat{\alpha} = \hat{\delta} / 1 - (\hat{\phi}_1 + \hat{\phi}_2 + \hat{\phi}_3)$ and refer to $\hat{\alpha}$ as the projected profit rate (PPR) and $\hat{\lambda} = 1 - (\hat{\phi}_1 + \hat{\phi}_2 + \hat{\phi}_3)$ as the speed of adjustment.

In the first subgroup of columns four and one it can be seen that the value of INPR changes from 4.14 (42 equations) in the AR(2) model to 3.591 (34 equations) in this model and PPR from 1.842 to 1.394. Examining columns one, two, and four we see that the value of the other subgroups have changed only slightly in their magnitude. By contrast the number of equations within the subgroup has also changed.

The significance in terms of the $\hat{\phi}$'s parameters of stationary equations are considered next. For the first lag's significance we found for this model a relatively small number of companies 79 or 38.5% whose coefficients were statistically different from zero and the coefficient of the second and third lags for the same equations were insignificant, so if the higher order parameters exhibit insignificance generally they can be removed from the equations. The correlations between $(\hat{\phi}_1, \hat{\phi}_2), (\hat{\phi}_2, \hat{\phi}_3)$ and $(\hat{\phi}_1, \hat{\phi}_3)$ are .047, .1403 and – .1926, respectively. These low correlations suggest that there exists less dependence between the parameters and the model does't need any simplification. We further found for a very negligible number of equations for which the second and third lag was statistically significant.

 $^{^1}$ Since we are dealing with annual data and our time period is very short we constrained our lag distribution up to maximum 3rd order.

Subsamples	â	â	R ²	INPR	N of firms
1	1.3943	.6232	.463	3.591	34
2	0.8317	.809	.379	1.116	34
3	0.1172	.786	.326	0.032	34
4	0.1666	.663	.431	1.007	34
5	-1.435	.705	.423	-1.852	34
6	-2.731	.626	.480	-3.850	35

Finally, we found 11 (5.4 percent) of the companies for which all three lag coefficients were statistically different from zero. They also depicts a very low correlation of -.07, .131 and -.322, suggesting less dependence between these parameters.

Now, we analyze a few of the 11 companies in terms of their PPR and INPR'S. The company Ruderus AG had a INPR which was -1.808 percent below the competitive mean and its PPR of -1.88 still remained below the completive mean after 22 years. This company was allocated according to INPR in the less persistent 5th subgroup. The PPR and INPR'S of models AR(1) and AR(2) resemble those of AR(3), but the statistical significance of the parameters differed among these models. For AR(1) and AR(2) the coefficients were not statistically different from zero whereas for AR(3) model they were all significant. Furthermore, all parameters fulfilled the stationarity conditions.

Ackermann-Goeggingen AG, whose INPR is below the competitive mean, had a positive PPR after 22 years. The estimates of AR(1) and AR(2) show that the PPR remains above the competitive mean and positive but the statistical significance differs again among the three models. Finally, Sued-Deutsch-Bremsen AG, which had an INPR above the competitive mean 1.894 percent, had a PPR of -.2026, which is below the mean. The estimates of the AR(1) and AR(2) indicate that their is virtually no difference in magnitude but we found once again difference in the statistical significance among these models. The speed of adjustment coefficient $\hat{\lambda}$ was quite close to zero. In conclusion it appears that some companies needs a adjustment period of longer than two years but this does not lead to persistence differences among these companies.

The following equation reveals the results of overall stationarity and significance of all 205 equations.

$$\begin{array}{c} (1-.348 \ \mathrm{B}+.0182 \ \mathrm{B}^2+.03219 \ \mathrm{B}^3) \ \mathrm{Z}_t = -.001098 + \varepsilon_t \\ (1.445) \ (-.0633) \ (-.1529) \ (-.1066) \end{array}$$

$$B_1 = 2.626$$
 $B_2 = 2.626$ $B_3 = 4.502$

The roots B_1 , B_2 and B_3 lie outside the unit circle, suggesting an accurate representation of the stationarity. The correlation coefficients of 205 equations between $(\hat{\varphi}_1, \hat{\varphi}_2)$, $(\hat{\varphi}_2, \hat{\varphi}_3)$ and $(\hat{\varphi}_1, \hat{\varphi}_3)$, which are .045, .073, -.152, respectively. This suggest that the overall representation with this higher degree lag of third order can be justified, since the correlation is low. This implies the absence of dependence between the parameters. The t-ratio's of the first, second and third lag imply that the restriction : $\phi_2 = \phi_3 = 0$ can be accepted for a substantial number of companies.

8.3.1 Specification test of AR(2) and AR(3)

A similar test (see section 5) was applied to check the model adequacy of each of 252 stationary equations of the AR(2) model and of the 205 equations of the AR(3) model, i.e., the errors of the models should be white noise and uncorrelated over time. The chi-squared tabulated values for AR(2) are 14.7 and 16.9, for 10 and 5 percent levels of significance with 9 degrees of freedom. We found for 9 companies at 10 percent level the calculated value exceeded the tabulated value which indicates the inadequacy for these equations and further at 5 percent level we found that for only 3 companies the null hypothesis has to be rejected.

For the AR(3) model the 6 companies for which the null hypothesis has to be rejected (10 percent level with 8 degrees of freedom) and at 5 percent level only for 4 companies the calculated value exceeded those of tabulated value of 15.5.

8.4 Results of ARMA(1,1)

Table 8.4 presents the results obtained from the mixed autoregressive-moving average model in which we included a moving average parameter in order to test whether the additional parameter improves the estimates.

The model is

 $Z_t = \delta + \phi_1 Z_{t-1} + \Theta_1 u_{t-1} - u_t$ or in backshift form

$$(1 - \phi_1 B) Z_t = (1 - \Theta_1 B) u_t + \delta$$

Our major concern is with the parameter ϕ_1 , so we will estimate the parameters of this model for each of the 299 equations. For the stability of the parameter ϕ_1 of AR term the roots of all equations were calculated. In 91 equations the parameter was found instable, so we dropped these equations from the sample. Table 4 contains the estimation results for this ARMA(1,1) model. The first column represents the estimates of $\hat{\delta} / (1 - \hat{\phi}_1)$, the projected profit rate (PPR), and column two represent $(1 - \hat{\phi}_1)$ or the speed of adjustment. The first column shows that the value of the first subgroup changes from 1.8 for AR(1) to 2.64 for ARMA(1,1). However, the number of companies of first subgroup also changes from 50 to 35. The value of the third subgroup is slightly larger than the second subgroup. This pattern is also observed with the AR(1) model, but the values of subgroup one, two and three are higher than with those of the subgroups of AR(1)

 $^{^1}$ The parameter redundancy was also checked (see Box and Jenkins (1976), p.248–250).

Table : 8.4

Subsamples	â	â	R ²	INPR	N of firms
1	2.642	.554	.509	4.580	35
2	0.613	.798	.424	1.627	35
3	0.777	.781	.371	0.226	35
4	0.105	.694	.450	-0.751	35
5	-1.230	.704	.418	-1.584	34
6	-2.496	.675	.487	-3.727	34

From the column two we see clearly that the values of the parameters of speed of adjustment for all the subgroups has changed and are larger in comparison with those of AR(1). This suggests that with this model the adjustment of the companies is faster then with the AR(1) model. Column four shows that the ordering of INPR across subgroups is consistent with those of the AR(1).

The overall significance and stationarity was estimated for all 208 equations by:

$$(1 - .298 \text{ B}) Z_t = (1 - .256 \text{ B}) \varepsilon_t + .00065$$

 $(1.55) (2.19) \varepsilon_t + .00065$
 $(.0851) B_1 = 3.356 B_2 = 4.33$

The t-ratio's in the parentheses indicate a well overall representation of the significance for both the AR and MA parameters. The roots also suggest that the stationarity conditions has also been fulfilled quite significantly. The correlation coefficient between $\hat{\phi}$ and $\hat{\Theta}$ of -.8023 is quite large. We can conclude that there is a high dependence between both parameters, suggesting that the $\hat{\Theta}$ parameter can be removed from the model.

8.4.1 Specification test of ARMA(1,1)

The same specification test was applied as in the previous section using 208 equations. With 9 degree of freedom the tabulated values are 14.7 and 16.9 for the 10 and 5 percent levels. For four companies the calculated value exceeded the 10 percent level and for 2 companies the 5 percent level, implying that these equations are statistically inadequate.

8.5 Test of lag structure

1

With the application of this test the lag structure (see section 3.8.3) or length of adjustment period of all comapanies will be examined.

The parameters ϕ and Θ of the ARMA(1,1) model were estimated. In order to calculate the asymptotic variance of Π_i the variance – covariance estimates from the model mentioned above were then used. Finally, the t-statistics were calculated for the truncation of the autoregression up to 22 lags. We then truncated the autoregression where the coefficient became statistically insignificant.

Of the 208 stationary series(or 59.5 percent), the distribution of lag structure varied between zero and four lags. For 62 companies (30 percent) the t-values were insignificant which may suggest that these companies do not posess any lag structure. For a significant number of companies 120 or 57 percent, there was a lag of one period¹. Further, for 23 companies or 11 percent a significant lag of two periods was found and for two companies a significant lag of three periods. Finally, for one company a significant lag of four periods was found.

The roots of the characteristic equation for the companies with their respective lag structure was calculated and revealed that for the first order all 120 equations were stationary and for the second order for 23 companies only three non-stationary series. Finally, third and fourth order degree polynomials provided stationarity. The PPR and INPR'S of the companies with all significant lags were similarly examined.

Geroski and Jacquemin (1987) also found a stronger evidence for first order lag.

Bayerische Harstein Ind. AG has an INPR of 4.15 percent and a PPR of 2.11 percent above the competitive mean, so this profitable company was allocated into the highest initial profit rate subgroup. The PPR and INPR of two companies with all three significant coefficients was similarly examined. The two companies, Chem.Werke Brockhues AG and Ges.f.Spinnerei u.Weberei AG had INPR'S of 3.28 and -1.79 percent and PPR'S of 10.39 and -.853 percent above (below) the competitive mean. The first company was allocated to the highest initial profit subgroup and the second one to the lowest subgroup, so the estimates of these companies suggests that a less or more persistent company does not have to depict higher significant lags, its rather arbitrary.

The most profitable Pharma/Chemical industry for the lag distribution was also analyzed of the 32 companies in this industry, 14 exhibited non-significant lags. From the remaining 14 companies, or 43 percent, exhibited a first order significant lag. The three companies exhibited significant lags. Finally, one company which had all his three lags significant. We found for a significant number of companies the initial profits below the competitive mean and their projected profits came up after 22 years above the mean, even these companies were assigned in the different initial profit rate subgroups. We further examined these companies according to their sales figures in 1980 and found the lag distribution quite arbitrary. To summarize the results of this test, it can be concluded that the larger companies have to depict lower lag and the smaller companies a higher lag. This implies that the successful companies adjustment is slow.

9.0 Regression results of stochastic models for US

9.1 Results of first order autoregressive model

In this section we report the results of the first order autoregressive model for the US sample of 500 companies over the time period¹ 1950 – 1980. We estimated each of the 500 series using 31 annual observations. For the stability of the parameters ϕ^2 the roots were calculated for all equations and we did not find any equation whose roots were less than unity. This means that all 500 equations were stationary. This means that all 500 equations were stationary.

From all 500 stationary equations the results are reported in table 9.1. The upper half of the table 9.1 contains the estimates of all 500 stationary equations, whereas the lower half only those equations for the ϕ parameter which is statistically different from zero. Column one of the table shows that the value of the first subgroup of 3.639 has increased in magnitude in comparison to the value of the first subgroup of 2.975 for the PA-model.

The value of other subgroups in column one resemble those reported in the first column of table 9.1. From column two of table 9.1 we see that the values of the means of the PA-model. The lower half of the table shows that the number of significant equations is 345 or 69 %, which is much higher than the PA-model of 230 or 46 %.

¹ This is the only study reporting the complete series from 1950 till 1980.

² The coefficients were corrected for small sample bias.

Table : 9.1

Subsamples	â	â	R ²	INPR	N of firms
1	3.639	.527	.572	6.266	. 84
2	1.693	.618	.432	2.289	84
3	0.863	.629	.388	0.450	83
4	0.071	.629	.341	-1.082	83
5	0.144	.580	.322	-2.531	83
6	-1.373	.523	.395	5.228	83
1	3.941	.403	.606	6.718	58
2	1.902	.488	.449	2.347	58
3	0.945	.447	.445	0.193	58
4	0.208	.517	.364	-1.378	57
5	0.388	.453	.392	-2.905	57
6	-1.263	.448	.407	-5.520	57

By contrast the means of the PA-model are larger in values with few number of significant equations, providing stronger evidence of persistence across subgroups in comparison with the subgroups of the autoregressive model. Columns one and four of the table also show that the ordering of $\hat{\alpha}$ is consistent except for subgroup 5 with those of the initial profit rates. Column two indicates that the mean values of $(1 - \hat{\phi}_1)$ are .46 and do not show any systemetic pattern across subgroups. Their values across subgroups are lower then the subgroups of PA-model. The overall significance of the estimates of the 500 stationary equations is identified by :

$$(1 - .415 \text{ B}) Z_t = -.00316 + \varepsilon_t$$
 B = 2.408
(2.80) (.384)

The number in the parentheses are the t-ratio's, which suggest an overall strong evidence of significance of the estimates. The root B = 2.408 also suggests that the stationarity has been very well represented.

9.1.1 Specification test of AR(1)

For the adequacy of the models we again applied the portmanteau test to all 500 equations. The tabulated value at 10% level with 14 degree of freedom is 21.1 and only for three companies did the calculated values exceed the tabulated values. This indicates that these three models may not yield a strong goodness of fit. At the 5% level with 14 degrees of freedom the tabulated value is 23.7, there is only one equation exists for which the calculated value (28.2) is greater, i.e., for this equation the model is inappropriate. The results in which we excluded the three and one equations respectively, are not reported, because no significant change among the subgroups was observed.

9.2 Results of second-order autoregressive model

Table 9.2 summarizes the results obtained from the second order autoregressive model for the US sample. The roots of all 500 characteristic equations were calculated, in only 9 equations were the roots less than unity. From the sample of 491 stationary equations the six subsamples were constructed. We will define again the projected profit rate (PPR) as $\hat{\alpha} = \hat{\delta} / 1 - (\hat{\phi}_1 + \hat{\phi}_2)$, the speed of adjustment as $\hat{\lambda} = 1 - (\hat{\phi}_1 + \hat{\phi}_2)$ and the initial profit rate (INPR) calculated as the average of the first three periods (50+51+52/3).

Column one of the table clearly indicates that the mean values of subgroups one to four have increased in magnitude in comparison with those of the AR(1) model. The ordering of subgroups remains consistent with those of the initial profit rate. The initial profit rate for the 82 companies in the third subgroup is .499 and after 31 years their projected profit rate is 1.179 above the competitive mean. This implies a stronger evidence of persistence with this model. Column two of the table shows that the values of the mean $\hat{\lambda}$'s are smaller than the values of the AR(1) model, implying a slower speed of adjustment with this model.

For the significance of first lag for thr $\hat{\varphi}$ parameter we found 17 equations or 35.4% which were statistically different from zero. The correlation coefficient between φ_1 and φ_2 for these 174 equations is -.312 suggesting a moderate relationship between them. This suggest that the model could be simplified to a single parameter. For the second lag's significance we found a smaller number of companies 51 or 10.4%. For a relatively large number of equations, 104 or 21.2 %, both coefficients were statistically significant their correlation coefficient is .415, suggesting a simplification of the model for these equations.

Table : 9.2

Subsamples	â	â	R ²	INPR	N of firms
1	4.171	.433	.593	6.193	82
2	2.537	.511	.439	2.324	82
3	1.179	.506	.406	0.499	82
4	0.247	.500	.358	-1.046	82
5	0.057	.441	.357	2.478	82
6	-1.568	.401	.414	-5.171	81

A company taken from a persistent subgroup for which both the coefficients are statistically significant has a value for INPR of 6.18 and after 31 years its PPR 5.29 still remained above the competitive mean. By contrast, company taken from a less persistent subgroup, has an INPR of -5.041, which is below the competitive mean and its PPR of -3.09 after 31 years still remained below the mean. This reveals that for a higher number of significant lags it is not important for a company to be less or more persistent.

The overall significance and stationarity for all 491 equations is identified by

 $(1 - .329 \text{ B} - .204 \text{ B}^2) Z_t = -.00282 + \varepsilon_t$ (1.79) (1.104) $Z_t = -.00282 + \varepsilon_t$ Roots : $B_1 = 2.209$ $B_2 = 2.209$

The numbers in the parentheses are the t-ratio's. The first lag exhibits a stronger significance than does the second lag. However, their low correlation coefficient of .064 reveals that there is no relationship between the parameters and the model does not need any simplification. Both roots B_1 and B_2 lie outside the unit circle, implying a strong overall representation of stationarity.

9.3 Results of third order autoregressive model

Table 9.3 reports the results of the third order autoregressive model estimated for each of the 500 equations. For 62 equations the roots were less than unity and were therefore dropped from the sample, six subgroups were than constructed from the 438 stationary equations. We defined $\hat{\alpha} = \hat{\delta} / 1 - (\hat{\phi}_1 + \hat{\phi}_2 + \hat{\phi}_3)$ as projected profit rate (PPR), $\hat{\lambda} = 1 - (\hat{\phi}_1 + \hat{\phi}_2 + \hat{\phi}_3)$ as speed of adjustment. Column one of the table indicates a distinct pattern where the mean values of subgroups one and three increase in comparison to the respective subgroups of the AR(2) model. On the other hand the mean values of subgroups two, four and five even decreases suggesting a lower persistence for these subgroups. Column two shows that the mean values of $\hat{\lambda}$ have decreased in all subgroups. Comparing with the $\hat{\lambda}$'s of the AR(2) model, this suggest that the speed of adjustment has decreased with this model. The ordering of $\hat{\alpha}$ across subgroups is not consistent with this model as well.

For 152 equations (34.7%) the first lag parameter is statistically different from zero. The correlation coefficient between $(\hat{\phi}_1, \hat{\phi}_2)$, $(\hat{\phi}_1, \hat{\phi}_3)$ and $(\hat{\phi}_2, \hat{\phi}_3)$ are -.144, -.538, .0208 respectively and the correlation between $\hat{\phi}_1$ and $\hat{\phi}_3$ is relative high, suggesting a simplification of the model. For a substantially fewer number of equations the second and third lag were statistically significant, but for a relatively large number of equations, 147 or 33.6%, all three lags were statistically insignificant. From their correlation coefficients which are .146, -.098, .221 respectively, we observe very weak relationships. In no equation were all three parameters were statistically significant.

Table : 9.3

Subsamples	â	â	R ²	INPR	N of firms
1	5.314	.364	.616	6.491	73
2	2.066	.454	.486	2.669	73
3	2.646	.383	.425	0.899	73
4	-0.142	.365	.407	-0.615	73
5	-0.886	.364	.374	-2.002	73
6	-0.272	.364	.422	-4.387	73

The overall stationarity and significance for all 438 equations is identified by:

$$(1 - .284 \text{ B} - .162 \text{ B}^2 - .171 \text{ B}^3) \text{ Z}_{t} = -.00304 + \varepsilon_{t}$$

 $(1.47) (.828) (.910) (.3104)$

Roots:
$$B_1 = 1.811$$
 $B_2 = 1.795$ $B_3 = 1.795$

From roots B_1 , B_2 and B_3 it can be seen that they all lie outside the unit circle, revealing a well overall representation of the stationarity. The correlation coefficients between $(\hat{\varphi}_1, \hat{\varphi}_2)$, $(\hat{\phi}_1, \hat{\phi}_3)$ and $(\hat{\phi}_2, \hat{\phi}_3)$ are -.064, -.560 ...,1248, implying that there is a strong relationship between the parameters $\hat{\phi}_1$ and $\hat{\phi}_3$. The model could perhaps be simplified. Finally, the t-ratio's of the first, second and third lag suggest that the restrictions $\phi_2 = \phi_3 = 0$ must be accepted for a substantial number of equations.

9.3.1 Specification test of AR(2) and AR(3)

The portmanteau test was applied to the 491 and 438 stationary equations for AR(2) and AR(3) models in order to check whether the errors of the models are white noise. The Chi-squared tabulated values for the 10 percent and 5 percent levels of significance with 13 and 12 degree of freedoms are 19.81, 22.36, 18.55, and 21.03 respectively. For the AR(2) model in only six equations does the calculated value exceed the tabulated value at the 10 percent level. At the 5 percent level the null hypothesis is accepted for all 491 equations. For the AR(3) equations there are no equations for which the calculated value exceeds the tabulated value, implying that the null hypothesis be accepted for all equations at both levels of significance.

9.4 Results of first order autoregressive-moving average model

Table 9.4 summarizes the results of the mixed autoregressive-moving average model of the following form

$$Z_t = \delta + \phi_1 Z_{t-1} + \Theta_1 U_{t-1} - u_t$$
 or in the backshift form

$$(1 - \phi_1 B) Z_t = (1 - \Theta_1 B) U_t + \delta$$

which was estimated for each of the 500 equations. For the stability of the ϕ parameter we calculated the roots and found for a substantial number of equations (148) that the root was less than unity. We eliminated these equations from the sample and made six subgroups as already explained in the previous sections. The upper half of the table 9.4 contains all 352 stationary equations and the lower half only those whose parameters ϕ was statistically significant. Column one shows that the ordering of the subgroups is not consistent with the INPR from column four. The mean value of subgroup two decreases from 1.693 in the AR(1) model to .952. By contrast, it increases substantially for the third subgroup, from .863 for the AR(1) model to 3.088. This implies that the initial profit rate of 1.093 for the 59 companies is above the competitive level, and after 31 years still earns 3.088 above the competitive mean. Column two indicates that the mean values of the $\hat{\lambda}$'s has substantially reduced across subgroups and is .4, implying a lower speed of adjustment. From the lower half of the table we observe similar behavior of the ordering of $\hat{\alpha}$ as reported above. The subgroup two exhibits a higher value than the second subgroup of upper half of the table.

Table : 9.4

Subsamples	â	â	R ²	INPR	N of firms
1	3.884	.337	.57	7.156	59
2	0.952	.425	.39	3.028	59
3	3.088	.386	.39	1.093	59
4	0.121	.342	.34	-0.362	59
5	0.453	.401	.32	-1.763	58
6	-0.487	.518	.40	-4.166	58
1	4.579	.189	.617	6.522	41
2	0.648	.281	.462	2.932	41
3	4.001	.224	.465	0.825	41
4	0.176	.165	.384	-0.722	40
5	0.406	.266	.379	-2.106	40
6	-0.386	.353	.424	-4.505	40

The mean value of subgroup four even becomes negative. Column two of the lower half shows that the mean values of $\hat{\lambda}$ across all subgroups becomes smaller in magnitude as compared to the mean values of the upper half, implying that these values in all subgroups are the lowest among all the model estimated so far further suggesting the lowest speed of adjustment. The average estimates of all 352 stationary equations is identified by

$$(1 - .598 \text{ B}) Z_t = (1 + .202 \text{ B})U_t + .00226$$

(3.69) (-.1856) t

Roots : $B_1 = -1.671$ $B_2 = 1.91$

the t-ratio of ϕ in parenthesis shows a strong overall significance of the equations, whereas for the Θ parameter the overall significance is poor. Further, the high correlation coefficient between $\hat{\phi}_1$ and $\hat{\Theta}_1$ of -.885, suggests a simplification of the model where the Θ parameter can be removed from the model. The average root of the equation is greater than unity, implying a strong overall representation of stationarity.

9.4.1 Specification test

Again the portmanteau test was applied to the residuals to check the model adequacy. The tabulated values with 14 degree of freedom at the 10 and 5 percent levels of significance are 21.1 and 23.7, and in no equation did the calculated value exceed it, implying that for all equations the null hypothesis should be accepted.

9.5 Test of lag structure

In order to answer a similar question (see section 8.5) the parameters ϕ and Θ were estimated from the model 31, P.37 for 500 US time series. The asymptotic variance of Π_1 was further calculated using the variance-covariance estimates derived from the model mentioned above. The expression 33 (see section 3.8.2) was finally calculated for 22 lags. The coefficients were truncated from that lag where the coefficient became statistically insignificant, 158 of 352 stationary series (or 44.8 percent) had a first lag statistically different from zero at the 5 percent level of significance. For 86 equations or 24.4 percent of the series the second lag was found to be statistically significant. By contrast, for the third and fourth lags there were 38 equations (or 10.8 percent) and 20 (or 5.7 percent) statistically significant. Further, for 36 equations (or 10.2 percent) no lag was statistically significant. This suggest that for a substantial number of companies the distribution of lags varied between zero and four.

We analyze next several companies whose all five and six lags were statistically significant. The two companies with all six significant lags are ETHYL–Corp. and FMC–Corp.. Their INPR are –.00339 and –.0275, which are below the competitive mean. After 31 years the ETHYL–Corp. became positive, whereas for the FMC–Corp. it remained negative. Further, both companies were allocated into the less persistent subgroups. We next examine the INPR and PPR of four companies whose all five lags are statistically significant. The INPR of the three companies SUNBEAM–Corp., MARATHIN OIL CO., and BRISTOL–MEYERS CO., are .1062, .058, .0665 respectively, which are above the competitive mean. After 31 years their PPR'S of .0388, .0542 and .0514, respectively, still remained above the competitive mean. The only company (QUAKER STATE OIL REFINING) with all five significant lags depicted the INPR –.00958, which is below the competitive mean and the PPR became positive. So, examining these estimates we once again conclude that only the companies with more persistent Π require lower lags for their adjustment period whereas the companies, with less persistent Π, needs higher lags for their adjustment.

9.6 Results of models selection test for FRG and US

In section 5. we applied the specification test to check the model adequacy. We now want to apply some other tests¹ to discriminate between the AR(1), AR(2), AR(3) and ARMA(1,1) models, in order to identify which model provides in the statistical sense the best fit. Chatfield and Prothero (1973) compared four models from the univariate class, firstly from a fitting point of view, and than from a forecasting point of view. They used the Q-statistics calculated from the residuals autocorrelation and the residual variance calculated as dividing the sum of square by the numbers of residuals. We calculated for our purpose only the estimates of residual variance for each of the four models for both countries time series. So, it was appropriate to look at the smallest value of the residual variance among these models. The results indicated that for the FRG the ARMA(1,1)² model seems to provide the smallest value for a relatively large number of firms, whereas for a quite significant number of US firms the smallest value for AR(3) model was found.

The other test we want to apply is of Hannan and Quin (1979) and looks like as follows :

HQ = Ln
$$\frac{\sum_{t=1}^{T} (Z_t - Z_t)^2}{T} + 2m \frac{Ln Ln T}{T}$$

where m is the estimated coefficient and T the number of observations.

Wolters (1984) used this test to discriminate the optimal lag length. He also discusses the disadvantages of other criteria like FPE of Akaike(1969) and BIC of Schwarz(1978).(See also Kirchgaessner(1984)).

¹ Shibata (1985) gives a short review on various model selection techniques.

² Granger and Newbold(1976) show that most economic series are both aggregates and are measured with error. It therefore follows that such mixed models will be found in practice. see also Fahrmeir, et.el. (1981, p.216).

We calculated the HQ- statistic for each of the time series for FRG and US using all four models mentioned above. The results once again confirm the finding of our test based on residual variance.

We see from the table 9.5, in which the numbers in the first row are the smallest values of HQstatistic, that in the second row there are only stationary equations, and in the third row the percentage values.Out of the 146 companies or 70.1 percent the smallest value of HQ-test was found for ARMA(1,1) model and for 33 or 16.1 percent the AR(2) model. In contrast, we found for 220 or 50 percent the smallest value for the AR(3) model of the US sample. In this sample only for 140 or 39.7 percent did the ARMA(1,1) model provide the better statistical fit. In the table we see that the test was applied to only stationary series from section 8.

Table: 9.5

17	D.	~	-
г	ĸ	ιx	Ξ
-		-	

ARMA(1,1) 146
146
208
70.1%
140
352
39.7%

9.7 Results of unit root test for FRG and US

A general problem in many time series applications is the question of whether a series should be differenced. This is equivalent to asking if the time series has a unit root (see Said and Dickey (1985)). If a time series exhibits trend, this can be eliminated through differencing, than to the differenced series the stationary process can be adjusted.

For most of the economic series the first order difference is sufficient to eliminate the trend. Wolters (1986) describes this problem of trend removal and uses the tests developed by Fuller (1976) for unit roots in the autoregressive part of time series (see also Kirchgaessner(1987,1988)). We uses a similar test from a survey article of unit root test by Dickey, Bell and Miller (1986). For discussion about the use of the test and the importance of detecting unit roots and other statistics (see Dickey and Fuller (1981), Evans and Savin (1981), and Said and Dickey (1984)).

We will compute the test statistics (see Dickey et el.(1986)) as:

 τ_{μ} = (φ - 1) / se , where φ is the estimated coefficient and se the standard error.

We test the null hypothesis $\phi = 1$ of non-stationarity against the alternative hypothesis of stationarity. So, if the calculated value of the test statistics is greater than the tabulated critical value at 1% (Fuller 1976, p. 373), then we should reject the null hypothesis, implying that the process is stationary.

We applied this test to the 299 FRG and 500 US time series, in which we calculated the statistics mentioned above. The results for Germany show that the hypothesis $\rho = 1$ can not be rejected at 1 % level of significance only for four firms of first order autoregressive model¹. For the autoregressive second and third order the hypothesis can not be rejected also at 1 % level for 9 and 13 firms respectively.

The results for the US indicate that for the first order autoregressive model the hypothesis $\rho = 1$ could be rejected for all 500 firms. Further, the hypothesis could not be rejected for 7 companies using the second order autoregressive model. Finally, for the third order model the hypothesis was not rejected for 17 companies. From these results we conclude that for a substantial number of companies the stationarity condition is fulfilled.

9.8 Summary

In this chapter we estimated the four different stochastic models from section 3 for both countries. We found that the magnitude of the subgroups mean increased for the first and last subsample across all models, but it was found to be more evident for the ARMA model for Germany. Similar behavior of the subsample means was found for the US but the most significant means were for the AR(3) model for the US. A low correlation between the estimated parameters of higher order models for both countries indicates that the models can be retained and do not need any simplification. The test of lag structure showed that a lower order lag is significant for Germany and that a higher order lag is also quit significant for the US. From the roots of the characteristic equations we found a substantial overall significance for both countries. Further, the results of the unit roots confirmed again the stationarity for both countries.

¹ We do not apply the unit root test for ARMA model (see Said and Dickey(1984)).

10. Identification results of ESACF-Procedure

In the previous chapter we estimated the univariate time series models without using the identification technique. In this chapter we apply the concept of extended sample autocorrelation function in order to identify the order and nature of the underlying process and than compare the results of these identified with non-identified models from previous chapter. We now apply the ESACF concept from chapter 4 first to a series A in Box and Jenkins(1976), consisting of 197 concentration reading taken every two hours from a chemical process and secondly, to the sample of 299 German and 500 US firms. Throughout this chapter table A will correspond as the ESACF table, table B as the Indicator Symbols and table C as the Error Limit Table. Additionally, throughout this chapter we will also search for a triangular cutting-off pattern with its vertex of ZEROS from table B.

The results for the 197 data points from table 10.1B show that the triangular¹ cutting-off pattern with its vertex at the ARMA(1,1) position. For the two points in the fifth and seventh column(table 10.1B) we see that the numerical values of these two points are only marginally larger than the two standard deviation values (table 10.1C) that are approximately equal to .14. Therefore, from the indicator symbol table we can infer that the appropriate order of the model is ARMA(1,1). Using the same series A, the estimated autocorrelations and partial autocorrelations of various differences are displayed in fig.6.2, p.179 and fig.6.3, p.184 of the Box and Jenkins (1976). These suggest that this time series might be described by an IMA(0,1,1) process and with another alternative as a mixed ARMA of order (1,0,1). Considering Box and Jenkins philosophy it means that a little ambiguity still remains with this technique.

¹ The rectangular or trapezoidal shape was also calculated and applied, but not a significant number of interpretable pictures were emerged. (see Tsay and Tio (1984),p.95).

					Table: 10).1		
					MA			· · · ·
AJ	R 0	1	2	3	4	5	6	7.
				A: THE	ESACF TAI	BLE		
0 1 2 3 4 5 6 7 8	$\begin{array}{c} 0.570 \\ -0.394 \\ -0.272 \\ -0.500 \\ -0.491 \\ -0.400 \\ -0.515 \\ 0.101 \\ -0.123 \end{array}$	0.495 0.042 -0.306 0.035 0.097 -0.236 0.262 0.020 0.010	+0.398 -0.059 -0.043 0.057 0.027 -0.156 -0.199 -0.149 -0.004	0.356 0.010 0.025 0.011 0.050 -0.020 0.089 0.274 0.256	$\begin{array}{c} 0.327 \\ -0.063 \\ -0.091 \\ -0.010 \\ -0.174 \\ -0.104 \\ 0.118 \\ 0.046 \end{array}$	$\begin{array}{c} 0.350 \\ -0.018 \\ -0.030 \\ -0.059 \\ -0.060 \\ -0.047 \\ -0.006 \\ -0.016 \\ -0.028 \end{array}$	$\begin{array}{c} 0.392\\ 0.152\\ 0.158\\ 0.154\\ 0.122\\ 0.083\\ 0.109\\ -0.006\\ -0.071 \end{array}$	$\begin{array}{c} 0.322 \\ -0.065 \\ -0.081 \\ 0.014 \\ 0.020 \\ -0.093 \\ -0.080 \\ -0.020 \\ -0.010 \end{array}$
				B: THE	NDICATO	R SYMBOL	S TABLE	
0 1 2 3 4 5 6 7 8	X X X X X X X 0 0	X 0 0 0 X X 0 0	X 0 0 0 0 X X X 0	X 0 0 0 0 0 0 X X	X 0 0 0 0 0 X 0 0 0	X 0 0 0 0 0 0 0 0 0	X 0 X 0 0 0 0 0 0	X . 0 0 0 0 0 0 0 0 0
				C: THE	ERROR LIN	AIT TABLE	1	
0 1 2 3 4 5 6 7 8	$\begin{array}{c} 0.142\\ 0.143\\ 0.143\\ 0.144\\ 0.144\\ 0.144\\ 0.145\\ 0.145\\ 0.145\\ 0.145\end{array}$	$\begin{array}{c} 0.174\\ 0.143\\ 0.156\\ 0.144\\ 0.145\\ 0.152\\ 0.152\\ 0.154\\ 0.145\\ 0.145\\ 0.145\end{array}$	$\begin{array}{c} 0.192\\ 0.144\\ 0.156\\ 0.144\\ 0.145\\ 0.155\\ 0.160\\ 0.148\\ 0.145\\ \end{array}$	0.205 0.144 0.156 0.144 0.146 0.146 0.156 0.161 0.159 0.155	$\begin{array}{c} 0.215\\ 0.144\\ 0.157\\ 0.144\\ 0.146\\ 0.160\\ 0.162\\ 0.160\\ 0.155\\ \end{array}$	$\begin{array}{c} 0.226\\ 0.144\\ 0.158\\ 0.145\\ 0.146\\ 0.160\\ 0.162\\ 0.160\\ 0.155\\ \end{array}$	$\begin{array}{c} 0.240\\ 0.147\\ 0.161\\ 0.148\\ 0.148\\ 0.161\\ 0.164\\ 0.160\\ 0.156\\ \end{array}$	0.248 0.148 0.162 0.148 0.148 0.162 0.164 0.161 0.156

We further applied the ESACF¹ procedure to the different macro time series taken from Wolters(1985)², for which the orders of the models were identified with the usual Box and Jenkins technique. In the following we report the equivalent identified order with ESACF Procedure. For the unemployment quote series with 90 observations we found with ESACF a ARMA(5,3) model, whereas Wolters(1985) identified with Box–Jenkins for the same series a ARMA(6,4) model. For the real gross national product with 99 observations we found a ARMA(4,3) model and with Box–Jenkins a ARMA(5,5) model. Similarly, for the two series amount of money and the price index of imports using 99 observations, we found with ESACF a ARMA(5,6) and ARMA(2,3), whereas with Box–Jenkins a ARMA(4,9) and ARMA(1,2) were identified.

We further applied the ESACF procedure to the sample of 299 German and 500 US firms.

We were faced with the problem of small samples³, i.e., the 22 annual data points for Germany and 31 for the US. Interpretable results were not found for all series, so we will only report in this chapter a few cases.

¹ The results were presented at doctoral lecture of the FU-Berlin.

² All these series contained seasonal components, see Wolters(1985).

 $^{^3}$ We extrapolated the 299 series in order to achieve better results, but finally constrained the analyses with original time series.

10.1 Identification results of FRG

Table 10.2A shows the ESACF and table 10.2B the corresponding indicator symbols of the firm ELSTER-AG MEB-u. REGELTECHNIK. If we look at the first row, which is actually the sample autocorrelation of the original series, we see that the ACF is only non-zero at first lag and becomes close to zero afterwards, and from column one we see at all lags we have a non-zero values. So if we look for the vertex of a triangle of asymptotic "ZEROS" values, we can identify from this table a moving average of first order, which certainly could have also been identified from the ACF of the Box-Jenkins procedure. For the four points in the column two, the numerical values (table 10.2A) are less than the two standard deviations from table 10.2C.

Using 22 annual data points the following estimation results are presented.

MA(1):
$$Z_t = .00771 + (1 - .7432 B)\varepsilon_t$$
 $R^2 = .346$
(.0065) (.1483)

The number within the parentheses are the estimates of the standard errors. The t-statistic of the moving average parameter is about 5.4 and is statistically significant. Further, a value of R^2 of .346 also suggest a good fit for the model.

The following four equations from the previous section, which were estimated without applying the identification technique, are presented below. The standard errors are within parentheses.

AR(1):
$$(1 - .4529B) Z_t = .00427 + \varepsilon_t$$

(.1971) (.0041) R²=.3004

AR(2):
$$(1 - .5577B + .2366B^2)Z_t = .00526 + \epsilon_t$$
 R²=.3388
(.2210) (.2207) (.00438)

$$\begin{array}{c} \text{AR(3):} (1-.598\text{B}+.333\text{B}^2-.177\text{B}^3) \text{ } Z_t = .00441 + \varepsilon_t \text{ } R^2 = .357\\ (.231) \quad (.260) \quad (.236) \quad (.0045) \end{array}$$

ARMA(1,1):
$$(1 + .305B) Z_t = (1 - .9548B) + \varepsilon_t$$
 $R^2 = .395$
(.230) (.0515)

Firm :Elster-AG-Meß-u.Regeltechnik

Table :10.2 MA 2 3 1 4 AR 0 A: THE ESACF TABLE 0 0.521 0.045 -0.1000.077 0.208 -0.093 1 2 3 4 0.524 -0.353 0.050 0.366 0.481 -0.084 0.003 0.003 0.042 0.091 -0.484 0.132 0.119 -0.151 -0.521 0.122 0.413 0.045 -0.022B: THE INDICATOR SYMBOLS TABLE X X X X X X 0 0 0 0 0 1 2 3 4 0 0 õ õ Õ Õ Õ Õ 0 0 0 0 0 0 0 Ó C: THE ERROR LIMIT TABLE 0 1 2 3 4 0.418 0.419 0.423 0.425 0.443 0.428 0.478 0.481 0.482 0.531 0.438 0.439 0.442 0.442 0.466 0.450 0.457 0.464 0.473 0.477 0.462 0.469 0.541 0.542 0.542

From the AR(1) equation we observe the t-statistic value is 2.29, which is statistically significant. The first coefficients of the AR(2) and AR(3) equations depict the t-statistics of 2.52 and 2.59 respectively, which are both significant. Further, the second coefficient of the AR(2) equation and the second and third coefficients of AR(3) which both have a relatively high standard error, are insignificant. From the ARMA model it can be seen that the MA parameter with its low standard error is highly significant, whereas the AR parameter depicts with its relative high standard error low significance. According to the low correlation of .2801 for the ARMA(1,1) model, the AR parameter can be dropped because of its insignificance.

The correlation coefficient between the AR(2) parameter is -.494, which suggest retaining the model. Further, the correlations between (ϕ_1,ϕ_2) , (ϕ_1,ϕ_3) and (ϕ_2,ϕ_3) are -.494, .1535 and -.492 ,indicating relatively less dependence between the parameters. Even the correlations between the parameters of AR(2), AR(3) and ARMA(1,1) are not very high. We can therefore conclude that the first parameter of ARMA(1,1) and the higher order parameters can be removed from the models because of their insignificance.

From the roots of the AR(2) and AR(3), which are $B_1=2.53$ and $B_1=1.47$, $B_2=1.71$ and $B_3=1.71$, we can infer that they lie outside the unit circle and that all models are stationary.

In addition, the value of \mathbb{R}^2 , which is around .35 for all four equations suggests a good fit for the models. From these results we conclude that there is a stronger evidence for a single lag specification and secondly, that the moving average model could also represent the data as well as the AR(1) model. For the MA model we conclude that the profit rate of this firm could have been generated from random shocks rather than from the previous lags.

With a INPR -.001149, which allocates this firm in the third subgroup, and after 22 years the PPR becomes positive for all models, indicating the success of this firm. In addition, the speed of adjustment coefficient remains around .5 for AR(1), but changes for AR(2) and ARMA(1,1), to .207 and .73 respectively. From these results we can conclude that the identified model fits the data as well as the autoregressive model of first order , i.e., the process and the order this time series generates have identical effects in both the MA(1) and AR(1) models.

To the identified MA(1) model we now add another moving average parameter to investigate the model adequacy. The results are presented below, and the standard errors are within the parentheses.

MA(2):
$$Z_t = .0071 + (1 - .723B + .194B^2) \varepsilon_t$$

(.01) (.225) (.216)

From the above results we see that the first coefficient remains statistically significant, with the t-statistics of 3.21, whereas the second coefficient, with its larger standard error becomes insignificant. The correlation coefficient of .942, which is very high, suggests that the insignificant parameter can be removed from the model, i.e., the identified model can be retained.
Using the 22 annual data points of the firm VOGTLAENDISCHE BAUMWOLL SPINNEREI AG, We search the vertex with zeros from table 10.3B. The triangular cutting-off pattern is observed at MA(1) or at MA(2). The numerical values of the two points in column two for the fourth and fifth rows are less than the two standard deviations, and if we consider a MA(2) model from table 10.3B, than we should expect the "X,s" in the second and third columns. But for illustrative purpose we will estimate both the MA(1) and MA(2) models.

After a MA(2) model has been identified, the estimated results of the MA(2) model are :

MA(1):
$$Z_t = -.01329 + (1 + .5084B)\varepsilon_t$$
 $R^2 = .514$
(.0055) (.1955)

MA(2):
$$Z_t = -.01329 + (1 + .518B + .3504B^2) \epsilon_t R^2 = .531$$

(.0063) (.213) (.213)

The numbers within the parentheses are again the standard errors of the estimates. The t-statistic of the MA(1) parameter of about 2.6 is significant. A statistically significant value of 2.4 of the first coefficient is found for the MA(2) model and according to the t-statistic of the second coefficient of 1.65, it is insignificant.

Further, a correlation coefficient between the parameters of .38 indicates less dependence between them. The roots of the characteristic equation lie outside the unit circle, which implies that the invertibility condition is fulfilled.

We now present the results of the following unidentified models, which are taken from the previous chapter:

AR(1):
$$(1 - .7249B)Z_t = .00473 + \varepsilon_t$$

(.1735) (.0038) R² = .6303

AR(2):
$$(1 - .4367B - .4739B^2)Z_t = -.00343 + \epsilon_t R^2 = .667$$

(.2093) (.2077) (.0033)

MA AR 0 1 2 3 4 A:THE ESACF TABLE	
AR 0 1 2 3 4 A:THE ESACF TABLE	*
A:THE ESACF TABLE	``
0 0.669 0.614 0.437 0.293 0.263 1 0.840 0.639 -0.072 0.321 0.224 2 0.574 0.688 0.475 0.340 0.179 3 0.846 -0.117 0.400 0.015 0.036 4 0.808 0.492 0.204 0.078 -0.115	
B: THE INDICATOR SYMBOLS TABLE	
0 X X 0 0 0	
1 X X 0 0 0	
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	
4 X 0 0 0 0	
C: THE ERROR LIMIT TABLE	
0 0.418 0.553 0.611 0.635 0.653	
1 0.428 0.577 0.578 0.610 0.625	
2 0.438 0.612 0.679 0.711 0.719	
3 0.450 0.450 0.522 0.	
4 0.402 0.505 0.579 0.581 0.586	

Firm : Vogtlaendische Baumwollspinnerei AG

From the AR(1) equation, we see that the t-statistic of the coefficient is 4.178 and

statistically significant. The two coefficients of the AR(2) model with their t-statistics of 2.08 and 2.28 are also significant. Further, the correlation between them of -.706 and is certainly high, suggesting the model simplification. The roots of the characteristic equation are B₁=1.06 and B₂= 1.98, i.e., they lie outside the unit circle indicating the stationarity of the models.

The results of the AR(3) and ARMA(1,1) are not reported, because they showed an explosive behavior of the estimates. If we now compare the results of the unidentified model with the identified model, we can conclude that the higher order autoregressive models do not represent the data as well as the lower order MA(1) and AR(1) models. Again, a strong evidence for the lower order models is found. From the INPR of -.02809 of this firm, which is allocated to the lowest group , we can see from the PPR of -.0719 and -.0715 for both models that this remains after 22 years in the same group. The speed of adjustment parameters for AR(1) and AR(2) are .275 and .09 respectively, whereas their PPR are -.00473 and -.00343. From these we conclude that if a firm depicts a lower speed of adjustment, it is not valid that its PPR has to be high.

In order to examine whether the identified model is adequate we estimate a more elaborate model using an additional MA parameter. The following equation contains the results for the MA(3) model:

MA(3):
$$Z_t = -.01329 + (1 + .2745B + .4074B^2 + .7819B^3)\varepsilon_t R^2 = .6544$$

(.0071) (.1915) (.1632) (.161)

The first coefficient with its t-statistic of 1.43 is insignificant. By contrast, the second and third coefficients, with t-statistics of 2.49 and 4.87 respectively, are significant.

There is a correlation coefficient of .229 between the first and second parameter, which indicate less dependence between them. Further, the correlation between the first and third parameter is .546, which is relatively high. We also estimated a MA(1) model, which depicted a significant t-statistic of 2.59. Considering all these results, we can conclude that only the MA(1) and two autoregressive model fits the data well.

Consider now the 22 observations for the time series of the firm " ANNELIESE ZEMENTWERKE AG". From table 10.4B a triangular cutting-off pattern can be seen from column two for the first row, which suggests a MA(1) model of the first order. Note that for the asterisk in the second column the numerical value is slightly less than two standard deviations and larger than the mean value, which is about .494.

An identified moving average model of first order was estimated and the results with standard errors within parentheses are:

MA(1):
$$Z_t = .01405 + (1 + .4165B) \varepsilon_t R^2 = .2447$$

(.0141) (.1892)

The coefficient of the MA parameter with its t-statistics 2.2 is significant.Further, the root is greater than unity, indicating that the invertibility condition is fulfilled.

Examining the results of unidentified models, which we take from the previous chapter, yields:

$$AR(1): (1 - .6145B) Z_{t} = .0217 + \varepsilon_{t} \qquad R^{2} = .3458$$

$$(.1516) \qquad (.00735) \qquad R^{2} = .3458$$

$$AR(2): (1 - .557B - .182B^{2}) Z_{t} = .04314 + \varepsilon_{t} \qquad R^{2} = .357$$

$$(.213) \qquad (.2104) \qquad (.00747) \qquad R^{2} = .357$$

2

AR(3):
$$(1 - .5311B - .135B^2 - .1622B^3)Z_t = .0.0821 + \epsilon_t R^2 = .3645$$

(.219) (.252) (.2144) (.00757)

ARMA(1,1):
$$(1 - .944B) Z_t = .126 + (1 - .462B)\varepsilon_t$$
 $R^2 = .2114$
(.093) (.244)

		Table: 10	0.4				
		MA					
AR	0	1	2	3	4		
		A: THE ESACF TABLE					
0 1 2	0.566 0.648 0.507	0.338 0.134 0.031	0.276 0.132 0.008	0.096 0.097 0.109	-0.130 -0.129 -0.174		
3 4	0.604 0.803	0.343 0.514	0.310 0.264	-0.368 0.321	0.130 0.078		
	<u></u>	B: THE INDICATOR SYMBOLS TABLE					
0 1 2 3 4	X X X X X	0 0 0 0 *	0 0 0 0 0	0 0 0 0 0	0 0 0 0 0		
		C: THE	ERROR LIN	AIT TABLE	1		
0 1 2 3 4	0.418 0.428 0.438 0.450 0.462	0.463 0.435 0.439 0.500 0.571	0.491 0.443 0.439 0.537 0.597	0.494 0.446 0.444 0.586 0.632	0.500 0.453 0.457 0.592 0.635		

Firm : Anneliese Zement-Werke AG

From the AR(1) model we see that the coefficient with a t-statistic of 4.05 is statistically significant. The second coefficient of the AR(2) model now becomes insignificant, whereas the first coefficient remains statistically significant. Further, a correlation coefficient between both of the coefficients is -.7482, which is certainly high and suggests a model simplification. A similar pattern is observed for the AR(3) model, i.e., the second and third coefficients become insignificant, whereas the first coefficient remains with its t-statistic significant. The correlations between (ϕ_1, ϕ_2) , (ϕ_2, ϕ_3) and (ϕ_1, ϕ_3) are -.558, -.529 and -.1779. The correlations between these parameters do not suggest a model simplification.

From the ARMA(1,1) model we see that both the autoregressive and moving average parameters with their t-statistics of 10.12 and 1.899 are significant. The correlation coefficient of .562 between them suggests that the model can be retained.

Further, we see from the roots of the AR(2) model that $B_1=1.26$, $B_2=4.3$ and for the AR(3) model that $B_1=1.25$, $B_2=2.34$ and $B_3=2.34$, and that they all lie outside the unit circle and are stationary. The root of the moving average parameter also fulfills the invertibility condition.

From these results we conclude that the lower model fits the data better than the higher order models. Further, the INPR of .0931, allocates this firm into the most persistent group. We can see from the PPR, which remains after 22 years above the competitive mean that this firm still remains successful. The speed of the adjustment coefficient of .05 is the lowest for the ARMA(1,1) model, indicating a higher persistence with its PPR of .126. So the conclusion that if a firm has a lower speed of adjustment its PPR has to be high, is valid for this firm, particularly for this model. We see for this firm that the selection of the process also plays an important role.

We now apply the overfitting method to the identified model, i.e., we extend the model with an additional moving average parameter. The following equation reports the estimation results:

MA(2):
$$Z_t = .01405 + (1 + .5265B + .2336B^2) \epsilon_t R^2 = .240$$

(.01127) (.210) (.2011)

We see from the results that the second coefficient becomes insignificant, whereas the first remains significant with the t-statistic of 2.504. Further, the correlation between the parameters is .365, suggesting that we retain the model.

The series analyzed is the profit rate of the firm BEIERSDORF AG with 21 annual data points (Outlier excluded). From table 10.5B we do not see a clear vertex of zeros, but if we consider the last two zeros of the first column and first row, their numerical values are less than two standard deviations. So we can perhaps suggests an ARMA(1,1) model from this table. Again the estimation results of the unidentified model from previous chapter are reported below. The standard errors are within parentheses.

ARMA(1,1):
$$(1 + .723B) Z_t = .04433 + (1 - .5201B)\epsilon_t R^2 = .918$$

(.185) (.0084) (.2158)

From the above results we see that both of the coefficients, with their t-statistics of 3.79 and 2.78, are statistically significant. The correlation coefficient of .426 between them is not very high and do not suggest a model simplification. Further, inspite of the restrictive use of \mathbb{R}^2 is around .918, which is very high and suggests a good fit of the model. From these results we conclude that this model fits the data quite adequately.

In the following we discuss the estimation results of the unidentified models from the previous chapter. The standard errors are within parentheses.

$$AR(1): (1 - .8703B) Z_{t} = .0720 + \varepsilon_{t} \qquad R^{2} = .8907$$

$$AR(2): (1 + 1.178B - .3709B^{2}) Z_{t} = .0945 + \varepsilon_{t} \qquad R^{2} = .9108$$

$$(.205) \qquad (.208) \qquad (.0054)$$

$$AR(3): (1 + 1.182B - .5037B^{2} + .1651B^{3}) Z_{t} = .0125 + \varepsilon_{t} \qquad R^{2} = .911$$

$$(.240) \qquad (.349) \qquad (.222) \qquad (.0062)^{t}$$

Firm : Beiersdorf	AG	r
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		Table: 10).5					
		МА						
AR	0	1	2	3	4			
		A: THE ESACF TABLE						
0	0.899	0.763	0.597	0.416	0.256			
1	0.692	0.351	0.027	-0.012	0.028			
2	0.609	0.106	0.213	-0.157	0.138			
3	-0.437	0.307	0.152	0.159	-0.153			
4	0.052	0.134	0.101	-0.003	-0.009			
		B: THE	INDICATO	R SYMBOI	S TABLE			
0	x	x	*	0	0			
1	x	Ô	0	ŏ	ŏ			
2	x	ŏ	ŏ	ŏ	ŏ			
3	0	Ō	0	0	0			
4	0	0	0	0	0			
		C: THE	ERROR LI	MIT TABLE	l			
0	0.418	0.615	0.709	0.750	0.765			
1	0.428	0.478	0.478	0.478	0.478			
2	0.438	0.443	0.462	0.473	0.480			
3	0.450	0.490	0.500	0.510	0.519			
		0.470	0 475	0 175	0.4775			

From the AR(1) model we observe that the coefficient with its t-statistic 6.49 is highly significant. Note that the first coefficient of AR(2) and AR(3) becomes large but still significant, whereas the higher order coefficients become insignificant. Further, we see that the correlation coefficient between ϕ_1, ϕ_2 is -.8308, which is certainly very high. Similarly, we observe from the AR(3) model that the correlations between (ϕ_1, ϕ_2) , (ϕ_1, ϕ_3) and (ϕ_2, ϕ_3) are -.813, .482 and -.796, suggesting a model simplification. The roots of the characteristic equations are $B_1=1.56$, $B_2=1.56$ for the AR(2) and $B_1=1.57$, $B_2=2.14$ and $B_3=2.14$ for the AR(3), i.e., they all lie outside the unit circle indicating the stationarity for these two models. Comparing the results of the identified model with others, we can conclude that the lower order models fit the data better. This firm is also assigned to the highest subgroup and after 22 years still remains above the competitive mean. From the speed of adjustment coefficient across the model, we find the lowest speed of adjustment for AR(3) model indicating no substantial change with its PPR.

Now we add a moving average and autoregressive parameter alternatively to the identified model. For the ARMA(2,1) the convergence was not achieved so we do not report the results here. In the following the estimation result of the ARMA(1,2) is reported. The standard errors are within the parentheses.

ARMA(1,2):
$$(1 - .7765B) Z_t = .00886 + (1 + .6339B - .3016B^2) \varepsilon_t R^2 = .833$$

(.2677) (.0118) (.3904) (.3617)

Expanding the model with the moving average parameter produces a insignificant coefficient with t-statistics as 1.62 and .833 respectively. The autoregressive parameter with a t-statistic of 2.9 remains statistically significant. Further, from the correlations between (ϕ_1, Θ) , (ϕ_1, Θ) and (ϕ_1, Θ) , which are .8166,.799 and -.778, a higher dependence between the parameters is indicated. So from these we can retain the identified model.

10.2 Identification results of US-Firms

We applied the ESACF-Procedure to the 500 US firms consisting of 31 annual data points and time period of 1950 through 1980. Even for these time series not a significant number of interpretable pictures were emerged. We tried using several variations to select the matrix dimension and finally constrained this up to a dimension of (5X5). We pick up again a few cases in order to describe the ESACF-features.

Consider now the 31 annual data points for the firm BRITISH PETROLIUM CO. LTD for which the Tables 10.6A, B and C report the results of the ESACF identification technique.

A moving average model of the first order is suggested with its Vertex of zeros from the indicator symbols table. A similar pattern of the four zeros in the second column is observed as for some German firms. The numerical values of these points (table 10.6A) are less than two standard deviation values which are about .3 (table 10.6C).

Again, the estimation results of the identified model are reported below. The standard errors are within parentheses.

MA(1):
$$Z_t = .0048 + (1 + .4107B) \epsilon_t R^2 = .137$$

(.0069) (.1730)

It should be observed that the moving average coefficient with its t-statistic of 2.37 is statistically significant. The invertibility condition of the parameter is also fulfilled, i.e., the absolute value of the parameter is less than unity. Further, a very modest value of R^2 is found implying a moderate fit of the model. These estimation results reveal that the profit rate of this company depends only on the random schocks of the previous years.

Firm : British petrolium co. ltd.

			Table :1	0.6	
		MA		4999-9999	
AR	0	1	2	3	4
		A:THE E	SACF TAI	BLE	<u></u>
0 1 2 3 4	0.404 0.381 0.489 0.553 0.576	$\begin{array}{r} 0.261 \\ -0.047 \\ -0.135 \\ 0.134 \\ -0.039 \end{array}$	0.282 0.284 0.221 0.057 0.176	-0.034 0.071 -0.093 0.159 0.128	0.107 0.100 0.104 0.112 0.262
	B : THE	INDICATO	R SYMBO	OLS TABLE	
0 1 2 3 4	X X X X X X X	0 0 0 0 0	0 0 0 0 0	0 0 0 0	0 0 0 0 0 0
	C: THE	ERROR LIN	IT TABL	E	
0 1 2 3 4	0.352 0.358 0.364 0.370 0.377	0.375 0.359 0.371 0.377 0.378	0.401 0.386 0.388 0.378 0.378	0.401 0.388 0.391 0.387 0.395	0.404 0.391 0.394 0.392

We now illustrate the estimation results of the following equations, which were estimated without using the identification technique. The t-statistics are within the parentheses.

$$AR(1) : (1 - .4283B) Z_{t} = .00505 + \varepsilon_{t} R^{2} = .1950$$

$$AR(2) : (1 - .3600B - .2136B^{2}) Z_{t} = .00598 + \varepsilon_{t} R^{2} = .2224$$

$$AR(3) : (1 - .3224B - .1402B^{2} - .2229B^{3}) Z_{t} = .006712 + \varepsilon_{t} R^{2} = .2504$$

$$AR(3) : (1 - .3224B - .1402B^{2} - .2229B^{3}) Z_{t} = .006712 + \varepsilon_{t} R^{2} = .2504$$

$$AR(3) : (1 - .3224B - .1402B^{2} - .2229B^{3}) Z_{t} = .006712 + \varepsilon_{t} R^{2} = .2504$$

$$AR(3) : (1 - .3224B - .1402B^{2} - .2229B^{3}) Z_{t} = .006712 + \varepsilon_{t} R^{2} = .2504$$

$$AR(3) : (1 - .3224B - .1402B^{2} - .2229B^{3}) Z_{t} = .006712 + \varepsilon_{t} R^{2} = .2504$$

$$AR(3) : (1 - .3224B - .1402B^{2} - .2229B^{3}) Z_{t} = .006712 + \varepsilon_{t} R^{2} = .2260$$

$$AR(4) : (1 + .7606B) Z_{t} = .00715 + (1 + .386B) + \varepsilon_{t} R^{2} = .2260$$

From the AR(1) model we see that the coefficient is insignificant. Only the first parameter of the AR(2) model is significant, whereas all other coefficients of AR(2), AR(3) and ARMA(1,1) are insignificant. The correlation between (ϕ_1,ϕ_2) for AR(2) is -.354 and for AR(3) between (ϕ_1,ϕ_2) , (ϕ_2,ϕ_3) and (ϕ_1,ϕ_3) -.272, -.314 and -.191. Finally, the correlation of the ARMA(1,1) model is .868 suggesting a high dependence between the parameters. From the roots of the AR(2) and AR(3) equations, which are B₁=1.47 ,B₂=3.16 and B₁=1.21 B₂,B₃=4.23 respectively, we see the stationarity of the the models i.e they all lie outside the unit circle. Comparing the identified model with the unidentified models we conclude that the MA(1) model fits the data efficiently.

This firm with its INPR of .00539 is allocated in the higher persistent group, but if we look at the speed of adjustment parameter, we do not observe a very significant difference among these models. In order to verify that the tentatively identified model contains the appropriate number of parameters to represent the data, we include an additional parameter in the MA(1) to see if its addition results in an improvement over the identified model. The following equation contains the results of the MA(2) model:

MA(2):
$$Z_t = .00484 + (1 - .2377B - .2703B^2)\epsilon_t$$
 $R^2 = .167$
(.645) (1.29) (.1883)

Both the moving average parameters with their t-statistics of 1.29 and .1883 are insignificant. Because the correlation coefficient is .2106 and not particularly high, we can conclude from the insignificance of moving average parameter that the identified MA(1) model can be accepted. Consider now the series for the firm QUAKER STATE OIL REFINING containing 31 annual data points. Even for this time series the identification is not straightforward from this table. The numerical values of the two points in column 5 are slightly larger than the two standard deviations, which are equal to .422 (table 10.7C). However, the numerical values of the two zeros in the first row and one zero in the first column are less than 2 X STD. Normally, we would expect for these zeros the "X", so from these results an ARMA(1,1) model could perhaps be suggested.

We now report the estimation results of this identified model. The t-statistics are within the parentheses:

ARMA(1,1):
$$(1 - .9356B) Z_t = .01087 + (1 + .5549B)\varepsilon_t R^2 = .6073$$

(11.6) (.424) (2.72)

The t-statistics of the autoregressive and moving average parameters are highly significant. However, their correlation is around .917 and very high, suggesting that the model can be simplified, because of the high dependence between them. A relatively high R^2 also suggest, a good fit for the model.

The estimation results of the following equations are reported for which the identification procedure was not applied. The t-statistics are within the parentheses:

$$AR(1): (1 - .6001B) Z_{t} = .0193 + \varepsilon_{t} R^{2} = .527$$

$$AR(2): (1 - .3776B - .3851B^{2}) Z_{t} = .0216 + \varepsilon_{t} R^{2} = .5908$$

$$AR(3): (1 - .2609B - .2600B^{2} - .339B^{3}) Z_{t} = .0267 + \varepsilon_{t} R^{2} = .629$$

			Table: 1	0.7				
			МА		· /			
AR	0	1	2	3	4			
		A: THE	ESACF TA	BLE				
0	0.588 0.485	0.567	0.578	0.405	0.466			
23	-0.497 0.283	-0.144	0.259	0.107 0.076	0.469 0.415			
4	0.423	B: THE INDICATOR SYMBOLS						
0	X X	X	X	0	 0 X			
23	X 0	0	0	0 0	X 0			
4	X	0 C. THE			0			
'n	0 252	0.451	0.525	0 572	0.617			
1 2	0.358 0.367	0.358	0.399 0.395	0.406 0.398	0.475 0.466			
3 4	0.370 0.377	0.387 0.377	0.425 0.392	0.427 0.402	0.479 0.411			

Firm : Quaker state oil refining

It should be observed that the AR(1) parameter is insignificant, whereas both of the coefficient of AR(2) are significant. From the AR(3) model we see that only the highest order parameter is significant. The correlation coefficient between the AR(2) parameters is -.247, and certainly not very high, which suggests that the model should be accepted. Further, the correlation between (ϕ_1, ϕ_2) , (ϕ_1, ϕ_3) and (ϕ_2, ϕ_3) are -.2124, -.1245, -.2307 and not particularly high. From the roots of the AR(2) model, which are as $B_1=2.19$ and $B_2=3.94$, we can see that they fulfill the stationarity condition. Similarly, from the roots of the AR(3) model, which are $B_1=1.76$, $B_2=3.05$ and $B_3=3.05$, we see that they lie outside the unit circle. Comparison of the identified model with other models suggests that the AR(2) model fits the data better than others.

From the INPR of -.00958 for this firm, we see that the PPR becomes positive for all models, indicating the success of this firm. From the speed of the adjustment parameter, which is very low for other models but lowest for the ARMA model, the hypothesis that the larger firms have the highest speed of adjustment indicating lower persistence is not valid for this case.

In order to check the model adequacy of the identified model, we will evaluate the following two models, each including an additional moving average and autoregressive parameters. The following equations contain the results of ARMA(2,1) and ARMA(1,2) models. The t-statistics are within the parentheses.

ARMA(2,1):
$$(1 - .842B + .0082B^2) Z_t = .0087 + (1 + .661B)\varepsilon_t R^2 = .196$$

(1.37) (.3078) $T_t = .00863 + (1 - .6392B - .424B^2)\varepsilon_t R^2 = .47$
(1.57) $(.421)$ (.396) $(.302)$

It should be observed that from the above equations that none of the coefficient is statistically significant. The correlations for the ARMA(2,1) model between (ϕ_1,Θ) , (ϕ_2,Θ) and (ϕ_1,ϕ_2) are .944, .761 and .901, suggesting a very high dependence between the parameters. A very similar behavior for the ARMA(1,2) is observed. So from these results we can conclude that the identified model can be retained.

Using 31 annual data points, the results of the ESACF are reported in tables 10.8A,B and C. Again the estimates of the ESACF table 10.8A are very similar with those already reported, i.e., the neighboring points covary rather declining gradually. The vertex of zeros is not clear as expected, so from these we can suggest the model is a moving average of first order. The following equation reports the estimation results of the identified MA(1) model. The number within parentheses are the t-statistics:

MA(1):
$$Z_t = -.0069 + (1 + .3563B) \epsilon_t \quad R^2 = .157$$

(1.2) (2.06)

The t-statistics of the moving average parameter indicate that the coefficient is statistically significant. Further, the coefficient also fulfill the invertibility condition that the absolute value of the coefficient is less than unity. A very modest value of R^2 indicates that the fit of the model is acceptable.

Some results of the unidentified models from previous chapter are now presented. The t-statistics are within the parentheses:

AR(1):
$$(1 - .4582B^2) Z_t = -.0129 + \varepsilon_t R^2 = .232$$

(2.785) $Z_t = -.026B^2 + \varepsilon_t R^2 = .232$
AR(2): $(1 - .3927B - .2026B^2) Z_t = -.008575 + \varepsilon_t R^2 = .254$
(2.095) (1.014) (-1.7)
AR(3): $(1 - .382B - .186B^2 - .0701B^3) Z_t = -.00938 + \varepsilon_t R^2 = .255$
(1.97) (.894) (.339) (-1.76)

Table: 10.8 MA 0 1 2 3 4 AR A: THE ESACF TABLE 0 0.419 0.264 0.163 -0.107-0.171-0.398 -0.001 0.172 -0.097 -0.1051 2 3 4 -0.093 -0.5190.200 -0.0850.010 0.540 0.400 0.363 -0.060 -0.056 -0.491 0.147 0.420 -0.062-0.149**B** : THE INDICATOR SYMBOLS TABLE 0 1 2 3 4 X X X X X X X X 0 0 0 0 0 Ō 0 0 ŏ Ō 0 0 ŏ ŏ 0 0 Ō 0 0 0 C: THE ERROR LIMIT TABLE 0.352 0.376 0.388 0.397 0 1 2 3 4 0.384 0.358 0.358 0.368 0.372 0.375 0.364 0.384 0.384 0.367 0.381 0.370 0.468 0.426 0.466 0.467 0.377 0.385 0.446 0.447 0,454

Firm : Boeing Co.

From the AR(1) model it can be seen that the parameter is statistically significant. The first coefficient of the AR(2) is also significant, whereas the higher order parameters of AR(2) and AR(3) are insignificant. The correlation coefficient of the AR(2) model, which is -.3931, indicates a less dependence. The correlations of the AR(3) for (ϕ_1, ϕ_2) , (ϕ_1, ϕ_3) and (ϕ_2, ϕ_3) are -.341, -.171 and -.224, which indicate less dependence. From the roots of AR(2), which are B₁=1.45 and B₂=3.34, we see that they lie outside the unit circle. Similarly the roots of AR(3) are B₁=1.32, B₂=3.27 and B₃=3.27, which also fulfills the stationary conditions. Because of the explosive behavior of the ARMA model the results are not reported.

Comparison of the models with each other shows that the lower order autoregressive model fits the data as well as the identified MA(1) model. According to the INPR of -.0296, for which also the PPR remains negative after 22 years ,there is no indication of any significant change for the speed of adjustment parameter.

We add another moving average parameter to the identified MA(1) model to see whether the additional parameters improve the results. The results of the estimated MA(2) model are presented below. The t-statistics are within the parentheses:

MA(2):
$$Z_t = -.00669 + (1 + .339B + .193B^2)\epsilon_t$$
 $R^2 = .158$
(.892) (1.79) (1.02)

The first coefficient of the model remains significant, whereas the second coefficient becomes insignificant. The correlation between them is .3055, which is not very high. As is known, if the higher order parameter is insignificant this can then be removed from the model.

Using again the 31 annual data points, the tables 10.9A,B and C report the results of the ESACF procedure. Not a very clear cutting-off pattern with its vertex of zeros emerges from the indicator symbol table. The numerical values of the two points of the first row are marginally less than the two standard deviations values for which are equal to the Mean = .428 and .561 and .588 (from table C). This implies that a ARMA(1,1) model could perhaps be suggested.

The estimation results of the identified ARMA(1,1) model are presented below. The t-statistics are within the parentheses:

ARMA(1,1):
$$(1 - .9665B) Z_t = .11555 + (1 + .456B)\varepsilon_t R^2 = .671$$

(16.46) (2.69) (2.17)

Both the autoregressive and moving average parameters are statistically significant. According to their correlation coefficient, which is .45, not a very high dependence exists between them. Further, a value of .671 for R^2 suggests a good fit for the model. From these results we conclude that the model fits the data considerably well.

We now analyze the results of the following fitted model for the same series, which is taken from the previous chapter. The t-statistics are again within the parentheses:

AR(1):
$$(1 - .757B)Z_t = .03277 + \varepsilon_t R^2 = .693$$

(1.79) (6.66)

AR(2):
$$(1 - .537B - .338B^2)Z_t = .0507 + \varepsilon_t R^2 = .712$$

(2.92) (1.86) (13.7)

AR(3):
$$(1 - .453B - .218B^2 - .272B^3) Z_t = .0924 + \varepsilon_t R^2 = .711$$

(2.29) (1.01) (1.37) (38.5)

Firm	:	Standard	Coosa-	Thatcher
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			Table: 1	0.9		
			МА			
AR	0	1	2	3	4	_
		A: THE	ESACF TA	BLE	<u> </u>	
0 1 2 3 4	0.682 0.416 0.487 0.456 0.406	$\begin{array}{c} \hline 0.577 \\ -0.081 \\ -0.221 \\ 0.362 \\ -0.124 \end{array}$	0.544 0.355 0.332 0.363 0.394	0.375 0.063 0.226 0.133 0.063	0.321 0.155 0.026 0.108 0.056	
		B: THE INDICATOR SYMBOLS				
0 1 2 3 4	X X X X X X	X 0 0 0 0	X 0 0 0 0	0 0 0 0 0	0 0 0 0 0	
		C: THE	ERROR LI	MIT TABL	3	
0 1 2 3 4	0.352 0.358 0.364 0.370 0.377	0.454 0.360 0.381 0.416 0.383	0.529 0.402 0.418 0.458 0.437	$\begin{array}{c} 0.561 \\ 0.404 \\ 0.434 \\ 0.463 \\ 0.438 \end{array}$	0.583 0.411 0.434 0.466 0.439	

The t-statistics of both the AR(1) and AR(2) parameters are statistically significant. The first coefficient of the AR(3) model remains significant, whereas the higher order coefficients become insignificant. The correlation between the AR(2) parameters is -.8458 and very high. Further, the correlations between (ϕ_1,ϕ_2) , (ϕ_1,ϕ_3) and (ϕ_2,ϕ_3) are -.5200, -.3625 and -.511. From these we can conclude that both models can be simplified. The roots of AR(2) and AR(3) models are as $B_1 = 1.09$, $B_2 = 2.68$ and $B_1 = 1.03$ $B_2 = 1.87$ and $B_3 = 1.87$, indicating that the models are stationary. Comparison of the models with each other shows that a lower order autoregressive model and the identified ARMA(1,1) model fit the data well. From the INPR of -.0307 for this firm, we see that for all the unidentified models the PPR become positive, but for the ARMA model the value of PPR substantially increases. According to the speed of adjustment coefficient of .0033, we see that the persistence of this firm becomes high.

To verify that the identified model contains the appropriate number of parameters, we include alternatively a MA(2) and AR(2) parameters. The following equations contain the results of the estimated ARMA(2,1) and ARMA(1,2) models. The t-statistics are within parentheses:

ARMA(2,1): $(1 - .8329B - .1286B^2) Z_t = -.0010 + (1 - .3608B) \varepsilon_t$ (1.92) (.332) (.666) (.880)

ARMA(1,2) : $(1 - .9519B) Z_t = .00144 + (1 - .525B + .1502B^2)\varepsilon_t$ (14.8) (.0017) (2.6) (.761) It should be observed that fitting an extra parameter to the autoregressive operator results in the insignificance of AR(2) and MA(1) parameters. The correlations between (ϕ_1, Θ_1) , (ϕ_2, Θ_1) and (ϕ_2, Θ_1) are .896, -.875 and -.990, which are certainly very high, so this suggest that a model needs to be simplified. Further, examining the correlations of the ARMA(1,2) model between (ϕ_1, Θ_1) , (ϕ_1, Θ_2) and (Θ_1, Θ_2) , which are .301, .297 and -.348, we see that these correlation are not very high, so from the insignificance of the MA(2) parameter this can be omitted from the model.

Comparing the results of the identified model with other models we can conclude that the AR(1) and AR(2) models fit the data just as well as the identified ARMA(1,1) model. Only AR(3) model could be reduced to a lower parameter model, because of the insignificance of the second and third parameters.

10.3 Summary

In this chapter the identification technique of ESACF was applied to samples for both countries. The results showed that this method does not give satisfactory results for small samples, but it identifies mostly a moving average of first order for both countries. We further compared the estimated results of this identified model with the estimates of stochastic models for both countries. The results suggests ambiguity between them because all models could be accepted statistically.

11. Comparison of FRG and US-results

11.1 POP comparison of PA-model

In this chapter the results between the FRG and the US are compared¹ for the time series 1961-80; 1961-82 of FRG and 1961-80, 1950-80 for the US.

In this section we will examine the question whether the persistent differences in profitability exist in Germany and the US from the PA-model estimates. Table 11.1 reports the replicated results from the previous chapter.

We first see that the ordering of $\hat{\alpha}$ across subsamples does not agree with that of INPR for both countries². A similar pattern is also observed for the significant equations (see numbers in the parenthesis). The persistence of subsamples increases significantly for the first two subgroups for Germany, i.e., the mean value of the first subgroup substantially increases from .532 to 2.154. A similar behavior is observed for the first three subgroups of US, if we consider only significant equations, i.e., the mean value of first subgroup becomes 4.64, which is very close to the mean value of the first subgroup of 1950–72 series. This implies that the difference in profitability across firms does not persist for these series but exists at least for both the most profitable and least profitable groups of firms.

¹see Odagiri and Yamawaki (1986) and Schwalbach, et.el.(1987). ² The results are not consistent with Mueller(1986).

Table: 11.1

FRG					USA				
Per	Period 1961–82				195080				
	N of Firms 299		99				500		
	Â	â	INPR	N	Â	λ.	INPR	N	
1	0.532 (2.15)	0.483	4.534 (3.1)	50	2.975 (4.6)	0.565	6.266 (6.9)	84	
2	0.363 (1.5)	0.730	1.618 (1.1)	50	1.566 (3.1)	0.636	2.289 (3.2)	84	
3	0.537 (.39)	0.666	-0.871 (01)	50	0.927 (2.8)	0.636	0.450 (1.2)	83	
4	0.238 (.02)	0.564	-1.871 (93)	50	0.188 (1.1)	0.639	-1.082 (-0.5)	83	
5	-0.413 (-1.3)	0.609	-1.178 (-1.9)	50	0.243 (.45)	0.605	-2.531 (-1.2)	83	
6	-1.125 (-2.3)	0.594	-1.374 (-3.4)	49	-0.736 (89)	0.576	-5.228 (-1.5)	84	

13.

The range of the mean values of $\hat{\alpha}$ becomes wider in both countries, particularly for the significant equations. The magnitude of the speed of adjustment coefficient does not vary greatly across subgroups and shows a similarity between the two countries. Further, the number of significant $\hat{\lambda}$'s are slightly higher in Germany than the US, implying that the profit rate adjustment toward the long-run level is almost equivalent in both countries. This result for the US is not consistent with 1950-72 series.

The difference in the results between Germany and US for this series is not very much different, i.e., the range of mean value of $\hat{\alpha}$, the speed of adjustment, the proportion of equations which have significant $\hat{\alpha}$ and $\hat{\lambda}$ and finally, the correlation between $\hat{\alpha}$ and $\overline{\pi}$ are all very much similar.

Furthermore, the US results show some important differences with the results¹ of the 1950–72 and 1964–80 series. The mean value of the first subsample is 4.68, which is much higher than that in the 1950–80 sample of 2.975 and of 1.48 for 1964–80.

Thus, we conclude from these results that the extent of the persistent difference in company profitability in Germany is less evident but considerably increases for the significant equations. A similar pattern is also observed for the US, i.e., the estimates are less significant for the 1950–80 series than in the 1950–72 series but substantially increases for the significant equations. Furthermore, these results for the 1950–80 series are consistent with those of Odagiri and Yamawaki(1990). These results are caused mainly by the difference of the time periods.

¹ For international comparison see Odagiri and Yamawaki (1990) and for more details obout other persistence of profit studies such as : For Canada , Khemani and Shapiro (1990), for France, Jenny and Weber (1990), for UK, Cubbin and Geroski (1990) and Kessides (1990).

11.2 POP comparison of stochastic models

11.2.1 Equivalent time period 1961-80 for FRG and US

In this section we will compare the estimated results of the stochastic AR(1) model for the equivalent time period 1961–80 of both the countries. Table 11.2 for the German results for this series show that the ordering of $\hat{\alpha}$ is not in accordance with that of INPR. These results are not similar to the series for 1961–82. The mean value of first subgroup, 2.163, is much higher than with those of the 1961–82 series, which is 1.787 and .47 of the PA-model. The value of subgroup four becomes negative as compared to other models. This implies that the results very sensitive to the period chosen and can not be generalized for the model chosen.

The results show that the extent of persistent profitability is noticeably evident, particularly for the first subgroup and moderately for the second and third subgroup as compared to the results of PA-model.

The US results (1961–80) show that the ordering of mean $\hat{\alpha}$ is not in perfect accordance with that of INPR. These results are also not consistent with the Mueller(1986) 1950–72 series and with the Odagiri and Yamawaki(1990) 1964–80 series. This suggests that for this US-series the difference in profitability across firms is less persistent. Furthermore, the mean value of $\hat{\alpha}$ in the first subgroup is 4.966 which is much higher than the mean value of PA – model and becomes very close to a value of 4.67 of 1950–72. series.

The speed of adjustment coefficient is around .744, whereas for 1964 - 80 series it was much lower .47 and for 1950 - 72 ia around .1802. This implies that with a high speed of adjustment coefficient we do not achieve a low persistence.

From these results of stochastic models we conclude that the extent of the persistent difference in company profitability also remains evident in the later periods for US than in the 1950–72 time period, but is not consistent with the 1964–80 periods.

		FRG 1961 — 19	80	USA 1961 — 19		
Subgroups	â	â	INPR	â	<u>م</u>	INPR
1	2.163	.467	4.388	4.966	.728	6.051
2	.5128	.725	1.574	1.772	.818	2.000
3	.6472	.659	.1508	.494	.828	.3751
4	3661	.530	862	.5228	.752	677
5	9105	.638	-1.776	0191	.7546	-1.917
6	2111	.628	-3.704	-1.344	.586	-4.425

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11.2.2 Results of complete time periods for both countries

In this section we will compare the results of stochastic models between two countries and then examine the existence of persistent differences in profitability across the stochastic models for Germany and the US. Table 11.3 summarizes the results of AR(1), AR(2), AR(3) and ARMA(1,1) for both the countries. These results are again the replicates from the previous chapter .

From the results of Germany and the US we see that the ordering of the $\hat{\alpha}$ across subsamples is not in perfect accordance with those of INPR for both countries, and this pattern is also valid for the significant equations. Further, this behavior also remains consistent across all four models for both countries. The mean value of $\hat{\alpha}$ in the first subsample has significantly increased from .532 of PA-model and varies between 1.394 to 2.6 across all models for Germany. Similarly, the mean value of first subgroup changes from 2.975 for the PA-model and varies between 3.639 to 5.314 across all models for the US. The highest mean value of 2.64 is found for the first subgroup of the ARMA model for Germany , whereas the highest value of the first subgroup was found for the AR(3) model for the US. Further, if considering only significant equations for AR(1) model the mean value of $\hat{\alpha}$ also increases from 1.78 to 2.334 for Germany and from 3.639 to 3.9 for the US. On the other hand, the number of firms also decreases as well for both countries. These results suggest that the extent of persistence of profitability increases substantially for the first subgroup across all models for both countries of the most successful firms and rises even for the significant equations. A similar pattern also existed for the lowest subgroups across all model for both countries.

The mean value of the speed of adjustment coefficient is higher in Germany and increases for higher order models. For the AR(1) model the mean value is low and decreases if only

		AR(1)			AR(2)	
			FRG			
Subgroups	â	â	INPR	â	î	INPR
1	1.787 (2.3)	.4230 (.35)	4.396 (4.9)	1.842	.525	4.143
2	0.379 (.23)	.7020 (.42)	1.558 (2.1)	.539	.813	1.234
3	0.392 (.50)	.6200) (.45)	.1160 (.13)	.649	.715	126
4	0.210 (.49)	.5240 (.41)	9000 (93)	216	.587	-1.091
5	9150 (76)	.5960 (.43)	-1.793 (-1.7)	1.46	.639	-1.903
6	-2.148 (-2.2)	.5570 (.37)	-3.735 (-3.6)	-2.76	.585	-3.926
			USA			
1	3.639 (3.9)	.5270 (.40)	6.266 (6.7)	4.171	.433	6.193
2	1.693 (1.9)	.6180 (,44)	2.289 (2.3)	2.537	.511	2.324
3	0.863 (.94)	.6290 (.44)	0.450 (.19)	1.179	.506	0.499
4	0.071 (.21)	.6290 (.57)	-1.082 (37)	0.247	.500	-1.046
5	0.144 (.38)	.5800 (.45)	-2.531 (-2.9)	.057	.441	2.478
6	-1.373 (-1.2)	.5230	-5.228 (-5.5)	-1.56	.401	-5.171

Cont.

FRG		AR(3)	AR(3)		ARMA(1,1)			
	â	â	INPR	â	λ	INPR		
1	1.394	.623	3.591	2.640	.5540	4.580		
2	0.832	.809	1.116	0.613	.7980	1.627		
3	0.117	.786	032	0.777	.781	0.226		
4	166	.663	-1.007	0.105	.694	751		
5	-1.435	.705	-1.852	-1.23	.704	-1.584		
6	-2.731	.626	-3.852	-2.49	.675	-3.727		
USA								
1	5.314	.3640	6.491	3.884	.337	7.156		
2	2.066	.454	2.669	0952	.425	3.028		
3	2.646	.383	0.899	3.088	.386	1.093		
4	142	.365	615	0.121	.342	-0.362		
5	886	.364	-2.002	453	.401	-1.763		
6	272	.364	-4.387	487	.518	-4.166		

significant equations are considered. This behavior is not observed for the US, i.e. the magnitude of speed of the adjustment coefficient becomes low for ARMA and higher order models. So, the hypothesis that if the $\hat{\lambda}$ approaches zero than the speed of adjustment is low and the persistence of profitability becomes high is valid for the US but not for Germany, at least for the best and worst subgroups.

For both the countries the $\hat{\alpha}$ ordering is again not in perfect accordance with INPR for all stochastic models and for the significant equations.

The results of stochastic models for the US shows some significant differences with the results of the PA-model of FRG and of the US 1950-72 and 1964-80 series. The mean value of $\hat{\alpha}$ becomes even higher for the higher order models. From these we conclude that for a significant number of equations the adjustment period is longer and this pattern differs across firms.

Further, the stationarity of the models was found higher in US than in Germany across all models. The magnitude of unstable roots were to be found higher in Germany than in the US, i.e., the sample for Germany was smaller than the US.

The numbers of significant equations were found high in US than in Germany. Further, evidence for the first lag structure was found to be stronger in Germany than in the US, but its pattern was strong in US.

11.3 Industry comparison

In explaining the persistent differences in profitability, it is argued that any kind of firm differences can be explained by industry differences. Some studies argue that the firm-effects are dominated other the industry-effects (see Geroski(1990) and Schmalensee(1986)). Schwalbach and Mahmood(1990) study showed that profit differences could be explained by firm and industry-specific effects.

In this section we try to answer similar question and show how the estimated projected profit rate (PPR) from stochastic models differs across industries and whether the estimates remain consistent across stochastic models and PA-model for the two countries. We first calculated the table 11.4 and 11.5 in which the firms were allocated to the relevant industry on the basis of a three-digit industry classification, and than calculated the mean $\hat{\alpha}$ for each of the industries for the after tax definition. We selected only those industries that could be matched with the US results¹ (1950-80 and 1961-80).

The estimates of mean value $\hat{\alpha}$ of beer and food industries² are the highest among all industries for FRG. These mean values vary between 1.238 till 1.459 for beer and 1.396 till 1.917 for the food industry across all stochastic models. If the significant equations of AR(1) and ARMA(1,1) for these industries are considered, the mean values changes, but only moderately. The estimates of the PA-model for these industries was also the highest for equity capital. Other positive mean values were also found for the chemicals, metal products and electrical equipment industries, and they remain consistent across all stochastic models.

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¹ The concordance among industries is not perfect for all industries (see Odagiri and Yamawaki (1990), and for problems of industrial classification (see Hay and Morris(1981)).

 $^{^2}$ The estimates of industrial differences are also shown for the equity capital(see Schwalbach and Mahmood (1990), and for discussion about branches studies see, Oberender, ed. (1984).
Table 11.4 : Industry Table for FRG.

	<u>1961–82</u>					<u>1961–80</u>
Industries	Code	<u>AR(1)</u>	<u>AR(2)</u>	<u>AR(3)</u>	<u>ARMA(1,1)</u>	<u>AR(1)</u>
Chemicals	200	0.5728 (1.15)**	0.222	0.836	0.6407 (.936)	0.6310 (1.74)
		37,19*	25	22	25,12	31,18
Stone & Clay	220	0242 (.617)	0943	532	1502 (.141)	7620 (44)
		18,12	16	12	14,7	18,11
Iron & Steel	230	4802 (.358)	1381	-2.328	-3.3920 (-6.11)	-1.580 (-1.1)
		13,8	12	8	7,2	13,7
Machinery	242	07832 (219)	3053	6051	15840 (426)	04790 (030)
		41,25	36	30	31,3	41,21
Electr. Equipment	250	.4583 (1.5)	.2194	.0123	.8252 (2.1)	.6643 (2.1)
		16,7	11	10	9,3	16,5
Metal Products	256	.3546 (.63)	.2215	.0464	1.011 (1.0)	.2938 (.84)
		10,5	8	7	6,2	10,4
Textiles	275	-1.1026 (-1.29)	-1.163	-2.021	-1.537 (-2.8)	8399 (55)
		35,21	32	25	24,10	35,19
Food	280	1.396 (1.1)	1.443	1.470	1.917 (2.5)	1.3250 (.953)
		12,8	8	9	9,4	12,8
Beer Brewing	293	1.459 (1.6)	1.44	1.463	1.238 (1.4)	1.9260 (2.23)
		14,12	. 11	9	10,9	13,10
		14,12	₄ 11	9	10,9	

**) Number within the parentheses are significant equations selected at 10% significance level

*) Number below the parentheses are the numbers of equations for nonsignificant and significant.

		<u>1950–80</u>			<u>1961–80</u>
Industries	<u>AR(1)</u>	<u>AR(2)</u>	<u>AR(3)</u>	<u>ARMA(1,1)</u>	<u>AR(1)</u>
Drugs and					
Chemicals	5.290 (6.3)	1.093	9.422	10.801 (16.1)	6.1430 (9.99)
	18,12	18	17	14,3	17,8
Cement, Clay					
and Glass	.9330 (2.2)	.164	1.073	.79800 (-2.3)	.4040 (.82)
	12,4 -	12	12	11,1	12,7
Iron & Steel	5610 (-3.6)	173	650	1790 (1.35)	9020 (-1.5)
	21,10	21	19	13,5	21,5
Machinery (non-electric)	1.570 (2.6)	.627	1.547	1.1340 (-3.2)	1.640 (.61)
	23,12	22	21	19,4	23,11
Electric					
Machinery	2.512 (3.9)	.189	3.866	2.026 (2.6)	1.62 (3.)
	9,6	9	8	7,2	9,1
Metal Products	9870 (2.05)	383	-1.206	7620 (48)	8450 (-2.1)
	8,3	8	7	5,4	8,2
Textiles	0700 (-1.3)	216	315	0930 (-2.6)	.7790 (1.3)
	9,3	8	8	8,1	8,2
Food	.6990 (1.5)	.227	.1904	.37200 (-1.7)	1.230 (.76)
	41,26	40	34	18,5	41,13

Table 11.5 : Industry table for USA

A significant factor is observed with the electric equipment industry, i.e., the mean value of this industry becomes positive for all these stochastic models and ranges between .0123 to .8252 across all models and significantly increases to a mean value of 2.118 for the significant equations of the ARMA model.

On the other hand a negative value, -0.332, was found for the PA-model. According to the estimates of the stochastic models this industry remains successful during this time period. Other characteristics from this table are the iron and steel industry which has the lowest estimates, and remains negative across all models for both the series 1961–82 and 1961–80. Other industries with negative estimates for 1961–82 series are machinery, textiles, and stone and clay products. By contrast, a positive mean value was found for stone and clay industry for the PA-model. From the results mentioned above, we see that the industries with their positive profits in 61-62 are expected to remain so in the future. Similarly, the industries with negative estimates remained also unsuccessful in the future. The comparison of stochastic models with the PA-model showed a significant difference, particularly for the stone and clay and electrical equipment industries.

Table 11.5 summarizes the estimated results of the 1950–80 and 1961–80 series for USA. The highest positive projected profits are found for the drug and chemical industry. The PPR ranges between 1.093 to 10.8 across all stochastic models and two series. These numbers even rise, if the significant equations(the numbers within the parentheses) of AR(1) and ARMA models are considered. Further, a distinctive factor is observed for the food industry., i.e., a high positive mean value was found for the AR(1) model of 1961–80 series, which remains also positive across all models, implying that this industry became more efficient in later periods, whereas Odagiri and Yamawaki (1986) and Mueller(1983) for the 1950–72 series found for the 1964–80 series a negative value of –0.007 and –0.0061 with the PA-model. Other profitable industries are cement, clay and glass, machinery (non–electric) and electric machinery.

The industries with the negative profitability are iron and steel, metal products and textiles. The textile industry also depicts a distinctive pattern, i.e., the PPR becomes positive for 1961-80 series, whereas Odagiri and Yamawaki(1986) found a negative value of -.978. This implies that this industry has become more efficient in the latter periods, if we rely on the estimates of stochastic models.

The common characteristics between the two countries for positive profits are that the food, drugs and chemicals, electrical industries depicts positive profits and show consistent results across all models. Only for the stone and clay products and metal products the results are quite apposite between two countries. On the negative side, the similarity exists between the iron and steel, and textiles industries. One other common characteristic is that the estimates remains consistent between two countries.

The results also show that the PPR do not remain consistent across the PA and Stochastic models for both series but vary across industries. The pattern differs across the two countries and between two series for US. The effect of the magnitude of significant equation is much higher in US than in Germany.

11.3.1 Summary

In this chapter we compared the results of the PA- model and of stochastic models. We found for the PA- model strong evidence of persistence in the significant equations for both countries. The results of an equivalent time period, 1961- 80, for two countries showed that the extent of the persistent differences in company profitability is greater in the US than in Germany. The results for the complete time period using stochastic models for both countries show that the magnitude of the mean of the first and last subgroup increases and is consistent across models. The magnitude of the speed of adjustment parameter is found to be lower for the ARMA and higher order models for the US than in Germany. The results of the industrial differences of means across stochastic models show that the mean of projected profit rate remains consistent for the periods 1961 - 80 and 1961 - 82 for Germany, whereas it was not found to be consistent, in particular for Drugs and Chemicals and the Electric machinery industries for the US. The results indicate considerable differences of profits between firms and industries.

SUMMARY AND CONCLUSION :

This empirical study applied univariate stochastic time series models to estimate the long-run profit rate and speed of adjustment of each of 299 German and 500 US companies. The study compared the results obtained with the results of PA-models and with other stochastic models as well. The empirical results of deterministic models for Germany show a slower speed of adjustment for the highest and slowest subgroups, implying a higher persistence of profit rates over time for the most successful firms and the less profitable firms. The US results for the PA-model (for 500 firms) show that the long run profit rates differ significantly across firms, implying a higher persistence of profits than in Germany, but also remain consistent with the results for the 1950–1972 series. The results of the lagrange multiplier test did not show a severe effect of autocorrelation in either sample, so we conclude that the misspecification caused by the autocorrelated error term is not substantial.

The results of the univariate time series analysis for both countries revealed that the increased numerical accuracy raised the persistence of profits in the most profitable and least profitable subsamples for both countries. It is further raised if only the statistically significant equations are considered in the analysis. The speed of adjustment coefficient tends to be smaller for the US than the FRG. The test of the lag structure showed that the first lag was highly significant and more so than the higher order lag for Germany, whereas it was found for the US, that the lag structure is also significant for the second and third order models. The non–stationarity test of unit root was rejected for both countries, implying that the stationarity conditions are strongly accepted for both countries. The model selection test showed that the ARMA model is chosen for Germany and for the US, but in addition a third order model was also accepted for the US.

The results from the extended sample autocorrelation function revealed that this procedure is not fully operational for small samples and is inconclusive in selecting the correct order. Only for large sample sizes does this procedure seem to work well. We can therefore conclude that this method remains in need of generalization and research should be directed to the theoretical investigation of the small sample behavior of this method.

Finally, we compared the PA- model with stochastic models of the persistent difference in company profits between the two countries. We found that the extent of the persistent difference in company profitability becomes more evident for Germany with stochastic models for the highest and lowest subgroups than with the PA-models. We also found that the strong persistence of profitability observed in the US for the 1952–72 period also became significant for the complete time period 1950–80 and for the 1961–80 period in contrast to the 1964–80 time period. Further, the industry differences results for Germany showed that for the electric equipment and stone and clay industries a significant difference in persistence is observed with stochastic models. For the US the distinctive factor is that the mean of the textile industry becomes positive in the later periods.

In conclusion we make the following comments:

The estimation results reveal that the lower order model best reflects the lag structure between previous and current profits for both the US and FRG. However, there was at least some evidence indicating that the AR(3) model may be valid under certain circumstances for the US, i.e., if we rely on the model selection test-statistics. This implies that the tendency of adjustment variation exists across some companies for the US, i.e., about 20 % of the companies needed longer time period to adjust to the market environment. An important qualification questioning the reliability of these results is the lack of any economic theory suggesting the appropriate number of lagged years to include in the autoregressive model but can be statistically tested. The estimation specification represented in the first order autoregressive-moving average model indicates the statistical superiority of this model, which incorporates the effect of unobserved but influential exogenous variables. Thus, it should be emphasized that first order autoregressive- moving average model results are probably economically more sensible and reliable than the third order autoregressive model.

So we conclude that the ARMA model can be justified because of its parsimonious properties. This result is also consistent with the study of Granger and Morris(1976) who show that the mixed ARMA model is the one most likely to occur. As most economic series are both aggregates and are measured with error it follows that such mixed models will often be found in practice. We stress again that the misspecification caused by the structural parameters of PA-model as well as by the error term can be partially resolved by using the stochastic models. Future research needs to be devoted towards explicitly identifying those economic variables directly influencing company profitability in addition to each firm's past profitability. Future studies need to explicitly include such firm- and industry-specific variables in models estimating company profitability.

Although the univariate time series models allow one to choose from a wide class of models, their parameter interpretation for higher order models is very restrictive and difficult and so they remain open for further research. They are not based on an underlying economic theory, nor does the theory tell us how long a lag should be. On the other hand, this method has various desirable properties such as detecting trend through differencing, the lagged variable need not be fixed, the error term can be autocorrelated, and finally, it has computational advantages.

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APPENDIX : I

STOCKCOMPANIES LIST OF FRG

NR.	IND.COI	DE COMPANY NAME
11	200	ENKA GLANZSTOFF AG
12	200	BASF
13	200	BAYER AG
14	200	SPINNSTOFFABRIK ZEHLENDORF
15	200	BEIERSDORF AG
16	200	CASSELLA FARBWERKE MAINKUR AG
17	200	DEGUSSA
18	200	DLW-AG
19	200	TH. GOLDSCHMIDT AG
20	200	HOECHST AG
21	200	KALI-CHEMIE AG
22	200	RIEDEL-DE HAEN AG
23	200	RUETGERSWERKE AG
24	200	SCHERING AG
25	200	SUED-CHEMIE AG
26	200	CHEM. FABRIKEN OKER UND BRAUNSCHWEIG
27	200	CHEM. WERKE BROCKHUES AG
28	200	CHEM. WERKE HUELS AG
29	200	GUANO-WERKE AG
30	200	HAGEDA AG
31	200	PAUL HARTMANN AG
32	200	KOEPP AG
33	200	F REICHELT AG
34	200	RUBEROIDWERKE AG
35	200	SCHEIDEMANDEL-MOTARD-WERKE AG
38	200	STIMPF AG
160	200	PHODIA AG
409	200	DVNAMIT NODEL AG
471	200	HAGEDORN AG
4/0	200	DIHDCHEMIE AC
405	200	SKM TROSTRERG AG
402	200	WOI EE WAI SDODE AG
493	200	
40	205	ESCO AG
42	205	
400	205	DELITSCHE TEVACO AG
205	205	
095	203	DECITIAN WEDVE AG
44	210	IOU A WERKE AC
40	210	DUNI OD AC
1026	215	MOUELINDETEENWEDKE KOAA
1033	215	MICHELIN KEIFENWEKKE KUAA
4/	215	CONTINENTAL GUMIMIWERKE AG
48	215	PHUENIX AG
49	215	ALLENTHAL-WEKKE AG
52	215	NEW TORK - HAMBURGER GUMMIWAREN COMPA
33	215	
54	215	
33	213	VENITAD UUMMIWEKKE AU
20	220	DICREKHUFF ZEMENIWERKE AG
57	220	NUKULEMENT AU
60	220	BATRISCHE HARTSTEIN INDUSKIE AG
62	220	BUNNER ZEMENTWERKE AG
64	220	EIEKNII AG

65	220	HANNOVERSCHE PORTLAND-CEMENTFABRIK AG
66	220	HEMMOOR ZEMENT AG
68	220	SOLENHOFER AKTIEN-VEREIN
69	220	TONWARENINDUSTRIE WIESLOH AG
70	220	TREUCHTLINGER MARMORWERKE AG
71	220	VEREINIGTE GROSSSALMER THONWERKE
73	220	BAUSTOFFWERKE MUEHLACKER AG
76	220	DIDIER-WERKE AG
78	220	ERLUS-BAUSTOFFWERKE AG
70	220	ERSTE BAYER BASALTSTEIN AG
81	220	MARMOR-INDUSTRIE KIEFER AG
83	220	TEUTONIA ZEMENTWERK AG
81	220	ZEAG ZEMENTWERK I ALLEENLEI EKTRIZITAET
64	220	ANNELIESE ZEMENTWERK LAUTTEN-ELEKTRIZITAET
625	222	DOSENTUAL DODZELLAN AG
033	223	ACDOD AC
85	224	
80	224	HUISCHENKEUTHER AG
87	224	KERAMAG, KERAMISCHE WERKE AG
88	224	PORZELLANFABRIK WALDSASSEN BAYREUTHER
89	224	ACTIENGES. NORDDEUTSCHE STEINGUTFABRI
90	224	PORZELLANFABRIK ZEH, SCHERZER + CO. A
91	224	DEUTSCHE SPIEGELGLAS AG
92	227	FLACHGLAS AG
93	227	GERRESHEIMER GLAS AG
94	227	GLAS- U. SPIEGEL-MANUFAKTUR AG
1059	228	SUEDMILCH AG
95	230	KLOECKNER-WERKE AG
96	230	AG DER DILLINGER HUETTENWERKE
97	230	BUDERUS AG
98	230	DITTMANN + NEUHAUS AG
100	230	GROSSMANN EISEN- U. STAHLWERKE AG
101	230	HINDRICHS-AUFFERMANN AG
102	230	KRUPP STAHL AG
103	230	PEINER MASCHINEN U. SCHRAUBENWERKE AG
104	230	RASSELSTEIN AG
106	230	ROESELER DRAHT AG
107	230	STAHLWERKE BOCHUM AG
109	230	A. STOTZ AG
1108	230	MANNESMANN AG
110	232	METALLGESELLSCHAFT AG
111	232	VEREINIGTE DEUTSCHE NICKEL-WERKE AG
112	232	ALLGEMEINE GOLD- U. SILBERSCHEIDEANS
113	232	HUETTENWERKE KAYSER AG
114	232	ALUMINIUMWERK UNNA AG
115	232	VEREINIGTE ALLIMINILIMWERKE AG
116	232	VEREINIGTE DEUTSCHE METALLWERKE AG
117	232	WESTEAELISCHE KUPEER, UMESSINGWERKE
711	222	NORDDEUTSCHE AFEINERIE AG
110	233	DUEWAG
110	240	ADNI CEODO AC
120	240	HEIN LEHMANN $\pm CO$ AC
120	240	LIDIN, LEIIMAININ T CO. AU
121	240	
122	240	RUELJUH-FUELLEK-WEKNE AU
120	242	DRUWN, DUVERIE + LIE AU
120	242	MEDIACHE BABUUUK AU
128	242	KLEIN, SCHANZLIN + BECKER AG
129	242	KLUECKNER-HUMBOLD-DEUTZ AG
130	242	LINDE AG
131	242	MASCHINENFABRIK AUGSBURG-NUERNBERG AG

132	Z4Z	O + K, URENSTEIN + KUPPEL AG
134	242	SCHIESS AG
135	242	SCHUBERT UND SALZER AG
120	242	ANTIENICEGELL COLLET & UPDINIC
130	242	ANTIENOESELLSCHAFT A. HERINO
139	242	AG KUEHNLE, KOPP + KAUSCH
140	242	ALEXANDERWERK AG
141	242	ALLWEILER AG
143	242	L BANNING AG
144	242	PENTELED WEDKE AC
144	242	
140	242	BRAUNSCHWEIGISCHE MASCHINENBAUANSTALT
147	242	BABCOCK BSH AG
148	242	AQUA BUTZKE-WERKE AG
149	242	MANNESMANN DEMAG AG
150	242	GEBR DICKERTMANN HEBEZEUGFABRIK AG
151	242	DISKUS WERKE ERANKEURT/MAINIAG
152	242	DODOTENED MACOUINENEADDIV AC
152	242	DORSTENER MASCHINENFABRIK AG
157	242	KOCHS ADLER AG
158	242	KOENIG + BAUER AG
159	242	KRAUSS-MAFFEI AG
160	242	LEHMANN-WERKE AG
161	242	LOSENHAUSEN MASCHINENBALLAG
163	242	MASCHINENEARDIK BUCKALLE WOLEAG
165	242	MASCHINENEADDIZ ESTEDED AC
104	242	MASCHINENFADRIK ESTERER AU
166	242	WIBAU AG
169	242	MASCHINENFABRIK-MUELLER-WEINGARTEN AG
170	242	MOTORENWERKE MANNHEIM AG
173	242	PITTLER MASCHINENFABRIK AG
175	242	M.A.N ROLAND DRUCKMASCHINEN AG
176	242	SUEDDEUTSCHE BREMSEN-AG
170	242	TORIMOU ADI ED AC
170	242	
1/9	242	VEREINIGTE SCHMIRGEL- U. MASCHENFABRI
181	242	WESTFALIA SEPARATOR AG
182	242	ZAHNRAEDERFABRIK RENK AG
654	242	JAGENBERG-WERKE AG
682	242	JOSEPH VOEGELE AG
183	244	BAYERISCHE MOTORENWERKE
18/	244	DAIMI EP-BENZ AG
104	244	
185	244	VULKSWAGENWERK AG
180	244	AUDI-NSU AUTO UNION AG
187	244	FICHTEL + SACHS AG
188	244	FORD-WERKE AG
189	244	RATHGEBER AG
190	244	ZAHNRADFARRIK FRIEDRICHSHAFFN AG
571	244	ADAM OPEL AG
102	246	AC WEGED
192	240	AU WEDER
193	240	BREMER VULKAN SCHIFFSBAU GESELLSCHAFT
194	246	ELSFLETHER WERFT AG
195	246	HARMSDORF AG
196	246	LEHNKERING AG
717	246	BLOHM & VOSS AG
720	246	FLENDER WERET AG
100	250	ALL GEM ELEKTDIZITAETOGEOELLOGUAETA
170	200	ALLOUM.ELENINIZIIAEISUESELLSUHAFI \A
199	230	BRAUN AU
200	250	HAKIMANN + BRAUN AG
201	250	KABEL- U. METALLWERKE GUTEHOFFNUNGSHU
202	250	SIEMENS AG
203	250	BAYERISCHE KABELWERKE AG
204	250	DELITSCHE TELEPHONWERKE IL KARELINDUST
205	250	PHILIPS KOMMINIKATIONS INDUSTRIE AC
	2. HJ	T T T T T T T T T T T T T T T T T T T

206	250	GARBE LAHMEYER + CO. AG
200	250	GRUENZWEIG UND GLASEASER UND HARTMANN
207	250	AEC TELEEINVEN VADELWEDVE AC
209	250	AEU-IELEFUINEIN KADELWERKE AU
210	250	LANGBEIN-PFANNHAUSER WERKE AG
211	250	LEONISCHE DRAHTWERKE AG
212	250	STANDARD ELEKTRIK LORENZ AG
547	250	BERGMANN KABELWERKE AG
556	250	NORDDEUTSCHE SEEKABELWERKE AG
213	252	AESCULAP-WERKE AG
214	252	PHYWE AG
215	252	G KROMSCHROEDER AG
216	252	PODI + WIENENBERGER AG
575	252	ELSTED AC MESS LIND DECELTECUNIT
515	252	ELSTER AU MESS- UND RECELTECHNIK
511	252	
280	252	H. MAIHAK AG
218	256	D. STEMPEL AG
219	256	WUERTEMBERGISCHE METALLWARENFABRIK AG
223	256	HALLER-MEURER-WERKE AG
226	256	METALL- U. LACKIERWARENFABRIK AG
228	256	CARL SCHLENK AG
229	256	R.STOCK AG
230	256	ZEISS IKON AG
511	256	OBERKIRCH AG
512	256	SCHULTE-SCHLAGBAUM AG
513	256	WILKENS BREMER SILBERWAREN AG
231	258	NICHT VORHANDEN
222	250	BIEDSTENEABDIK EMIL KDAENZI EIN
235	260	KATZ WEDEE AG
233	200	
230	200	J. F. MUELLER + SUMN AU WESTAC - CETALIT AC
231	200	WEDIAU + GEIALII AG
241	204	KNOECKEL, SCHMIDT + CIE PAPIERFABRIKE
242	264	NIEDERMAYR PAPIERFABRIK AG
244	264	PAPIERFABRIK WEISSENSTEIN AG
246	264	SCHWAEBISCHE ZELLSTOFF AG
247	264	WESTFAELISCHE ZELLSTOFF AG
977	264	EUROPA CARTON AG
249	265	KUNSTANSTALTEN MAY AG
250	265	H. SCHOETT AG
251	265	UNIVERSITAETSDRUCKEREI H. STUERTZ AG
252	265	VEREINIGTE ALTENBURGER U. STRALSUNDER
253	265	VERLAG UND DRUCKEREIG, L MANZ AG
254	265	ZUCKER + CO AG
256	271	SALAMANDER AG
257	271	DELITER INDUSTRIEWERKE AG
250	271	
239	275	
200	213	
201	2/5	GIRMES-WERKE AG
262	2/5	KOLB + SCHUELE AG
264	275	AUGSBURGER KAMMGARNSPINNEREI
265	275	GERMANIA-EPE SPINNEREI AG
266	275	BAUMWOLLLSPINNEREI GRONAU
271	275	BRAUNSCHWEIGISCHE AG FUER JUTE UND FL
272	275	BREMER WOLLKAEMMEREI
273	275	BSU-TEXTIL AG
274	275	CALWER DECKEN- U.TUCHFABRIKEN
275	275	CONCORDIA SPINNEREI II. WEBEREI
277	275	ERBA AG
280	275	GESELL SCHAFT FUER SPINNERFLU WEBEPE
281	275	GRUSCHWITZ TEXTIL WERKE AG
	41.1	N H N N J N N H H H H J J J J J J J J J

284	275	JUTE SPINNEREI U. WEBEREI BREMEN
288	275	KOLLNAUER SPINNEREI U. WEBEREI
289	275	KULMBACHER SPINNNEREI
292	275	MECH. SEIDENWEBEREI VIERSEN AG
293	275	NEUE BAUMWOLLSPINNEREI U. WEBEREI
294	275	NEUE SPINNEREIBAYREUTH AG
295	275	RAVENSBERGER SPINNEREI AG
296	275	SCHOELLER EITORF AG
298	275	SPINNEREI NEUHOF
299	275	SPINNEREI U. WEBEREI KEMPTEN
300	275	SPINNEREI U. WEBEREI MOMM AG
301	275	SPINNEREI UND WEBEREI PFERSEE AG
302	275	VEREINIGTE FILZFABRIKEN AG
303	275	VEREINIGTE RUMPUSWERKE AG
304	275	VEREINIGTE SEIDENWEBEREIEN AG
305	275	VOGTLAENDISCHE BAUMWOLLSPINNEREI
306	275	WEBER + OTT AG
307	275	WOLLDECKENFABRIK WEIL DER STADT AG
745	275	GOLD-ZACK WERKE AG
751	275	NAK STOFFE KGAA
763	275	TEXTI WERKE AHAIIS AG
310	276	TRIIMPH INTERNATIONAL AG
211	280	HOEEMANNS STAEDVEEARDIVEN AG
212	280	STOLI WEDCK AG
212	200	A ACUENED THEDMALWARGED (VALCEDDDINNEN
214	200	ACHENER THERMALWASSER (RAISERDRUIVIEN
214	200	
217	280	
210	200	DIAMALT AC
318	280	DE BLAUEN QUELLENE MEVED : CO AC
319	280	DIE BLAUEN QUELLEN F. METER + CO. AG
321	280	
324	280	HOURSEEFISCHEKEI NUKUSTEKIN AG
320	280	MINEKALBRUNNEN UEBERKINGEN-TEINACH AG
328	280	OELMUEHLE HAMBURG AG
329	280	SINALCO AG
331	281	AG KUNSTMUEHLE
333	281	LANDSHUTER KUNSTMUEHLE C. A. MEYER
334	281	MUEHLE RUENINGEN AG
335	281	STUTTGARTER BAECKERMUEHLEN AG
336	281	VEREINIGTE KUNSTMUEHLEN LANDSHUT-ROSE
337	285	SUEDDEUTSCHE ZUCKER AG
339	285	POMMERSCHE PROVINZIAL-ZUCKERSIEDEREI
340	285	ZUCKERFABRIK UELZEN AG
1083	288	GERVAIS - DANONE AG
1085	289	WALTER RAU NEUSSER OEL UND FETT AG
1079	291	C. GROSSMANN AG
1081	291	NORDFLEISCH AG
342	293	BERLINER-KINDL BRAUEREI AG
343	293	BINDING BRAUEREI AG
344	293	BRAU AG
346	293	DORTMUNDER AKTIENBRAUEREI
352	293	HOLSTEN BRAUEREI
354	293	LOEWENBRAEU MUENCHEN
356	293	STERN-BRAUEREI CARL FUNKE AG
391	293	HAAKE-BECK BRAUERELAG
300	293	KOENIGSBACHER BRAUERELAG
409	293	PAULANER-SALVATOR-THOMASBRAEU
413	293	STUTTGARTER HOFBRAFU AG
415	203	WIERZBURGER HOERRAFU AG

1090	293	BAVARIA-ST.PAULI BRAUEREI AG
1096	293	HACKER-PSCHORR BRAEU AG
416	294	GEORG GEILING + CO. AG
417	294	CH. A. KUPFERBERG + CO. KGAA
418	294	KURPFALZ SEKTKELLEREI AG
419	294	SEKTKELLEREI J. OPPMANN AG
420	294	SEKTKELLEREI SCHLOSS WACHENHEIM AG
1080	294	MARTINI & ROSSI AG
1078	295	APOLLINARIS BRUNNEN AG
1000	000	

1082 299 RINN & CLOOS AG

APPENDIX : II

STOCKCOMPANIES LIST OF USA

NR. COMPANY NAME

-999	N.A
375766	GILLETTE CO
812302	SEARLE (G.D.) & CO
781088	RUBBERMAID INC
853564	STANDARD KOLI SMAN INDS INC
633304	NOVELL CODD CL D
0/0140	ADMADA CODD
042065	ARMADA CORP
8/3382	TANDT CORP
867068	SUNBEAM CORP
848355	SPERRY CORP
408360	HAMMOND CORP
832377	SMITHKLINE CORP
487836	KELLOGG CO
165159	CHESAPEAKE CORP OF VA
-999	N.A
849339	SPRAGUE ELECTRIC CO
483044	KAISER CEMENT CORP
752159	RANCOINC
822737	SHELLER-GLOBE
156866	INGERSOLL PAND CO
565945	MADATUON OT CO
102042	HEREMAN (C) DEWING INC
422004	CUANDION SDADE DI LIC
138003	CHAMPION SPARK PLUG
/90155	ST JOE MINERALS CORP
854531	STANLEY HOME PRODUCTS INC
574599	MASCO CORP
427866	HERSHEY FOODS CORP
780240	ROYAL CROWN COS INC
530000	LIBBEY-OWENS-FORD CO
620076	MOTOROLA INC
579746	MCCORD CORP
493422	KEYSTONE CONS INDUSTRIES INC
585745	MELVILLE CORP
861589	STONE CONTAINER CORP
580628	MCGRAW-EDISON CO
852206	SOUAREDCO
8306/3	SKII COPP
370442	GENERAL MOTORS CORD
178124	IOUNS MANUELE CODD
4/0124	JOHNS-MANYILLE CORF
400210	DOCKWELL DEEDMATIONAL CODD
1/434/	ROCKWELL INTERNATIONAL CORP
884315	THOMAS & BETTS CORP
489314	KENNECOTT CORP
629853	NALCO CHEMICAL CO
361606	GF BUSINESS EQUIPMENT
905530	UNION CAMP CORP
054303	AVON PRODUCTS
313549	FEDERAL-MOGUL CORP
451542	IDEAL BASIC INDUSTRIES INC
955465	WEST POINT-PEPPERELL
589433	MEREDITH CORP
028861	AMERICAN PETROFINA-CL A
822635	SHELL OIL CO
00000	

597715	MIDLAND-ROSS CORP
263534	DU PONT (E.I.) DE NEMOURS
853683	STANDARD OIL CO (CALIF)
211813	CONTINENTAL OIL CO
_000	N A
820575	SKELLY OIL CO
707255	
101333	ANDCO DITTEDUDCU COPD
032037	AMPCO-PITISBURGH CORP
709903	PENNZOIL CO
746384	PUROLATOR INC
278058	EATON CORP
640745	NEPTUNE INTERNATIONAL CORP
-999	N.A
770553	ROBERTSON (H.H.) CO
604059	MINNESOTA MINING & MFG CO
963320	WHIRLPOOL CORP
853819	STANDARD PRESSED STEEL CO
119529	BUFFALO FORGE CO
559380	MAGNAVOX CO
313135	FEDDERS CORP
165339	CHESEBROUGH-POND'S INC
217210	COPELAND CORP
717265	PHELPS DODGE CORP
070203	BASSETT FURNITURE INDS
7/0203	PROCTER & GAMBLE CO
500202	MILES I ADODATODIES INC
500925	MILES LABORATORIES INC
290622	MEDIA MACHINE CO
090510	N A
-999	
110311	BRITISH AMERICAN TODACCO LTD
413873	MARKIS CURP
101216	
191210	CUCA-CULA CU
232105	CUILEK-HAMMER INC
668367	NOR THWESTERN STEEL & WIKE CO
905581	UNION CARBIDE CORP
460146	INTL PAPER CO
717081	PFIZER INC
690020	OUTBOARD MARINE CORP
770519	ROBERTSHAW CONTROLS
701111	PARKER PEN CO
248631	DENNISON MFG CO
-999	N.A
892892	TRANE CO
156879	CERTAIN-TEED CORP
809877	SCOTT PAPER CO
232525	CYCLOPS CORP
235811	DANA CORP
193558	COLEMAN CO INC
925853	VICTOR COMPTOMETER CORP
365550	GARDNER-DENVER CO
155177	CENTRAL SOYA CO
582272	MOI OUTH STEEL COPP
227220	TIMEEN CO
067122	WEVEDUACHCED CO
102645	WEIERNAEUJEK UU
123043	BUILER INTERNATIONAL INC
019330	MUKTON-NOKWICH PRODUCTS
532457	LILLY (ELI)& CO

912027 U S GYPSUM CO

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144285	CARPENTER TECHNOLOGY
219327	CORNING GLASS WORKS
694529	PACIFIC LUMBER CO
-999	NA
576216	MASSEY FERGUSON LTD
029717	AMERICAN ATANDARD CO
637747	NATIONAL STANDARD CO
037355	WALL ACE MURRAY CORP
302200	EXXON COPP
022015	SIN OF OO
000013	TEV ACO INC
661094	LONE OTAD INDUCTDICS
342290	DUVE STAK INDUS IKIES
/25100	PILISBURGH FORGINGS CO
427056	HERCULES INC
369604	GENERAL ELECTRIC CO
763172	RICHARDSON-MERRELL INC
580169	MCDONNELL DOUGLAS CORP
043339	ARVIN INDUSTRIES INC
629156	NL INDUSTRIES
835495	SONOCO PRODUCTS CO
-999	N.A
604739	MIRRO CORP
345370	FORD MOTOR CO
150033	CECO CORP
488620	KENDALL CO
167898	CHICAGO PNEUMATIC TOOL CO
-999	N.A
775422	ROHR INDUSTRIES
099725	BORG-WARNER CORP
077455	BELDEN CORP
373712	GERBER PRODUCTS CO
244199	DEERE & CO
141375	CARBORUNDUM CO
438506	HONEYWELL INC
859264	STERLING DRUG INC
693506	PPG INDUSTRIES INC
001707	BLACK & DECKER MEG CO
254723	DISTULERS CORP. SEAGRAMS I TD
234723	COMPTON & KNOWLES CORP.
761406	DEVEDE CODDED & DDASS INC
150575	CHAMDION INTEDNATIONAL CODD
126140	CHAMPION ENTERNATIONAL CORP.
022097	AMDEY CODD
052087	AMIFEA CORF
-999	
400734	INTERSTATE BRANDS
304300	DAVDESTOS MANUATTANING
754580	CENESCO DIO
3/1532	GENESCU INC
5/1443	MARQUEITECO
5/53/9	MASONITE CORP
501026	RECENTER MEDICION
5/3298	GEORGIA-PACIFIC CORP
344892	FUOTE MINERAL CO
370622	GENERAL REFRACTORIES CO
277461	EASTMAN KODAK CO
171196	CHRYSLER CORP
513696	LAMSON & SESSIONS CO
608302	MOHAWK RUBBER CO
693715	PABST BREWING CO

-999	N.A
488188	KELSEY HAYES CO
300587	EX-CELL-O CORP
959265	WESTERN PUBLISHING INC
- 9 99	N.A
228669	CROWN ZELLERBACH
302808	FABERGE INC
579780	MCCORMICK & CO
775371	ROHM & HAAS CO
433728	HOBART CORP
589331	MERCK & CO
033047	ANCHOR HOCKING CORP
170520	CHRIS-CRAFT INDS
629527	NABISCO INC
561246	MALLORY (P.R.) & CO INC
819785	SHARON STEEL
667451	NORTHWEST ENGINEERING CO
880370	TENNECO INC
-999	N.A
749285	RCA CORP
682505	ONEIDA LTD
834086	SOLA BASIC INDUSTRIES INC
044540	ASHLAND OIL CO
934408	WARNER & SWASEY CO
031105	AMETEK INC
-999	N A
216669	COOPER INDUSTRIES INC
826690	SIGNODE CORP
690734	OWENS-CORNING FIBERGLAS CORP
758260	REED TOOL CO
315711	FIBREBOARD CORP
379568	GLOBE-UNION INC
637844	NATIONAL STEEL CORP
231021	CUMMINS ENGINE
149123	CATERPILLAR TRACTOR CO
134429	CAMPBELL SOUP CO
209759	CONSOLIDATED PAPERS INC
457659	INSU CO CORP
854616	STANLEY WORKS
_000	N A
776338	RONSON CORP
867323	SUNDSTRAND CORP
206813	CONE MILLS CORP
-999	N A
547779	LOWENSTEIN (M) CORP
362400	GABLE INDS
751277	RALSTON PURINA CO
402460	GULF OIL CORP
181396	CLARK FOUIPMENT CO
718507	PHILLIPS PETROLEUM CO
_000	N A
961548	WESTVACOCORP
110220	BRITISH PETROLEUM COLTO ADP
-000	N A
857861	STANADVNE INC
271252	GENERAL TIRE & RURBER CO
600769	OWENS II LINOIS INC
450200	INTERDEDINORS INC
407080	MODIL OIL CODD
1 H I / I IAI I	

318315	FIRESTONE TIRE & RUBBER CO
737628	POTLATCH CORP
761688	REXNORD INC
143483	CARNATION CO
636316	NATIONAL GYPSUM CO
606215	MISSOURI PORTLAND CEMENT CO
029465	AMERICAN SEATING CO
580645	MCGRAW-HILL INC
903443	UARCO INC
459884	INTL MINERALS & CHEMICAL
039483	ARCHER-DANIELS-MIDLAND CO
609150	MONARCH MACHINE TOOL CO
747402	OUAKER OATS CO
118745	BUCYRUS.FRIF CO
157/70	INI AND STEEL CO
430000	HOOVED
048825	ATLANTIC PICHEIELD CO
040023	DI LIE DELL INC
421506	LIAZEI TINE CODD
421390	CHEDING DUOLICH
292402	COLID DIC
202492	TOTINGON & TOTINGON
4/8100	JOHNSON & JOHNSON
559/11	FLININUID CO
511690	MATER (USCAR) & CO
491102	ION MEC CO
481190	DROUDLCDOUD DIC
110007	BROWN GROUP INC
110097	DUDEN CODD
126202	CANADIAN DEENEDIES 1 7D
133393	UCANADIAN DREWERIES LID
425200	MADCOD INC
019204	MARCOR INC.
910204	
000	N A
609744	MAI VCADD INC
000744	TIME INC
601224	MATIONAL CASH DECISTED CO
491070	IOSI VNI MEC & SLIDDI V CO
401070	DIAMONID INTEDNATIONAL CODD
232009	EXERCISE ECTRIC CO
291011	NODTUDOD CODD
000007	NUK INKUP CUKP
075015	DEATRICE FOODS CO
073013	SIMMONS CO
010775	
912//3	DOWN FORMAN DISTILLEDS OF P
427215	NATIONAL PRESTO INDO INC
212602	FEDERAL DADER DOADD CO
515095	ADMETRONG DUDDED
702/52	ARMSTRUNG RUDDER
193433	DOISE CASCADE CODD
245514	EQDEMOST MOVESSON INC
260956	CENED AL ECODO CODD
202020	CERECAL FOODS COKP
130023	CERRU CURF
004/93 106000	DAY ANNAR FUUDS & INDS
400090	CDANITEVILLE CO
201410 260902	
20170012	CALLETE DEALINUS

100/19	REPUBLIC STEEL CORP
824348	SHERWIN-WILLIAMS CO
719151	PHOENIX STEEL CORP
172172	CINCINNATI MILACRON INC
239577	DAYCO CORP
056147	BABCOCK & WILCOX CO
000	N A
-999	
189486	CLUETI, PEABODY & CO
713448	PEPSICO INC
261597	DRESSER INDUSTRIES INC
736245	PORTER (H.K.) INC-DEL
315405	FERRO CORP
724479	PITNEY-BOWES INC
104162	COLCATE BALMOLIVE CO
194102	COLUMPERAL CARLE CORR
369298	GENERAL CABLE CORP
393046	GREEN GIANT CO
307261	FANSTEEL INC
763121	RICHARDSON CO
077851	BELL & HOWELL CO
150843	CELANESE CORP
201000	CDEAT NORTHERN NEKOOSA CORD
391090	N A
-999	N.A
217687	COPPER WELD CORP
458506	INTERCO INC
866645	SUN CHEMICAL CORP
872649	TRW INC
582834	MEAD CORP
370838	GENERAL SIGNAL CORP
853734	STANDARD OIL CO (OHIO)
450420	ITE BADEDIAL CODD
430420	I-I-E INFERIAL CORF
483008	KAISER ALUMINUM & CHEM CORP
460578	INTERPACE CORP
747419	QUAKER STATE OIL REFINING
853700	STANDARD OIL CO (INDIANA)
500755	KRAFT INC
200273	COMBUSTION ENGINEERING INC
224300	CRANECO
400191	CRIMMANCORD
400101	
08/509	BETHLEHEM STELL CORP
831865	SMITH (A.O.) CORP
-999	N.A
860163	STEVENS (J.P.) & CO
784015	SCM CORP
960402	WESTINGHOUSE ELECTRIC CORP
081680	RENDLY CORP
001002	N A
-999	
-999	
494368	KIMBERLY-CLARK CORP
902878	UMC INDUSTRIES
-999	N.A
137735	CANNON MILLS CO
963150	WHEELING-PITTSBURGH STEEL
549866	LUKENS STEEL CO
250270	EDITEUATE CODD
3373/0	
458702	INTERLAKE INC
033609	ANDERSON, CLAYTON & CO
860486	STEWART-WARNER CORP
370064	GENERAL HOST CORP
297659	ETHYL CORP

	and a second
377600	GLENMO
252741	DIAMOND SHAMROCK CORP
260543	DOW CHEMICAL
500602	KOPPERS CO
626320	MUNSINGWEAR INC
-999	N.A
370334	GENERAL MILLS INC
492386	KERR-MCGEE CORP
-999	N.A
-999	N.A
217525	COPPER RANGE CO
120457	BULOVA WATCH CO
853139	STANDARD BRANDS INC
060221	BANGOR PUNTA CORP
097023	BOEING CO
483098	KAISER STEEL CORP
909160	UNIROYAL INC
053501	AVCO CORP
693718	PACCAR INC
909296	UNITED AIRCRAFT CORP
761753	REYNOLDS (R.J.) INDS
855668	STARRETT (L.S.) CO
758556	REEVES BROTHERS INC
459578	INTL HARVESTER CO
907770	UNION OIL CO OF CALIFORNIA
709317	PENNWALT CORP
440452	HORMEL (GEO. A.) & CO
457641	INMONT CORP
121691	BURLINGTON INDUSTRIES INC
173036	CITIES SERVICE CO
382550	GOODYEAR TIRE & RUBBER CO
933169	WALTER (JIM) CORP
253651	DIEBOLD INC
610304	MONROE AUTO EOUIPMENT CO
212867	CONWOOD CORP
861504	STOKELY-VAN CAMP INC
761763	REYNOLDS METALS CO
302491	FMC CORP
668707	NORTON SIMON INC
144465	CARRIER CORP
716769	PETTIBONE CORP
408306	HAMMERMILL PAPER CO
257867	DONNELLEY (R.R.) & SONS CO
635655	NATIONAL DISTILLERS & CHEMICL
718167	PHILIP MORRIS INC
410306	HANDY & HARMAN
718592	PHILLIPS-VAN HEUSEN
-999	N.A
423236	HELENE CURTIS INDUSTRIES
245217	DEL MONTE CORP
_000	N A
228219	CROWN CENTRAL PETROLEUM CP-A
077491	DELDING HEMINWAYN
032393	ANACONDA CO
903298	USM CORP
_000	N A
_000	NA
054303	AVONDALE MILLS
893341	TRANS UNION CORP
	and the second

766481	RIEGEL TEXTILE CORP
691497	OXFORD INDUSTRIES INC
.000	N A
532202	LIGGETT GROUP
370856	CENERAL STEEL INDS
105010	COLUMNS PADIO CO
193018	COLLINS KADIO CO
-999	N.A OOI UMBLA DDDOOTING SVOTEM
19/288	COLUMBIA BRDCSTING SYSTEM
912056	U S STEEL CORP
211183	CONTINENTAL CAN CO INC
375046	GIDDINGS & LEWIS INC
493782	KIDDE INC
480034	JONES & LAUGHLIN STEEL CORP
032172	AMSTAR CORP
810640	SCOVILL INC
125185	CF&I
093545	BLISS & LAUGHLIN STEEL CORP
235773	DAN RIVER INC
829302	SINGER CO
200200	EVANS PRODUCTS CO
404245	HAW INDUSTRIES INC
000	
-777	COLUMNS & ATVMAN CODD
194020	COLLING & AIRMAN CORP
202711	FAIRCHILD INDUSTRIES INC
290371	ELIKA CORP
884102	THIOKOL CORP
835852	SORG PAPER CO
701094	PARKER-HANNIFIN CORP
852563	STALEY (A.E.) MFG CO
608030	MOHASCO CORP
753329	RAPID-AMERICAN CORP-DE
539821	LOCKHEED CORP
157177	CESSNA AIRCRAFT CO
428182	HEUBLEIN INC
745791	PULLMAN INC
097880	BOND INDUSTRIES
231561	CURTISS-WRIGHT CORP
562876	MANHATTAN INDUSTRIES INC
_000	N A
754002	
734093	
200210	CONSOLIDATED ECODS CODD
209219	CONSOLIDATED FOODS CORP
-999	N.A
904784	UNILEVER N V
934488	WARNER-LAMBERT CO
889039	TODD SHIPYARDS CORP
423074	HEINZ (H.J.) CO
368838	GENERAL AMERICAN TRANS CORP
486638	KAYSER-ROTH CORP
076635	BEECH AIRCRAFT CORP
211291	CONTINENTAL COPPER & STL IND
370118	GENERAL INSTRUMENT CORP
864592	SUCREST CORP
374280	GETTY OIL CO
122781	BURROUGHS CORP
857721	STAUFFER CHEMICAL CO
383883	GRACE (W R) & CO
117042	RDINSWICK COPP
020600	AMEDICAN SHID DUU DINC CO
022002	AWERICAN SHIP BUILDING CO

530013	LIBBY, MCNEILL & LIBBY	
361428	GAF CORP	
887360	TIMES MIRROR CO	
635128	NATIONAL CAN CORP	
-9 99	N.A	
088665	BIBB CO	
460043	INTL MULTIFOODS CORP	
-999	N.A	
071707	BAUSCH & LOMB INC	
350244	FOSTER WHEELER CORP	
416162	HART SCHAFFNER & MARX CO	
081437	BEMIS CO	
291210	EMHART CORP	
296470	ESMARK INC	
744635	PUBLICKER INDUSTRIES INC	
286434	ELGIN NATIONAL INDUSTRIES	
755111	RAYTHEON CO	
549662	LUDLOW CORP	
902525	U&IINC	
228255	CROWN CORK & SEAL CO INC	
725701	PITTSTON CO	
525030	LEHIGH VALLEY INDS	
073239	BAYUK CIGARS INC	
115223	BROWN & SHARPE MFG CO	
237424	DART INDUSTRIES	
502210	LTV CORP	
826622	SIGNAL COS	
369334	GENERAL CIGAR CO INC	
883203	TEXTRON INC	
680665	OLIN CORP	
759200	REICHHOLD CHEMICALS INC	
676346	OGDEN CORP	
369550	GENERAL DYNAMICS CORP	
196864	COLT INDUSTRIES INC	